Overview of SAR Observation of Ocean Winds

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NOAA/NESDIS Alaska SAR Demonstration Workshops
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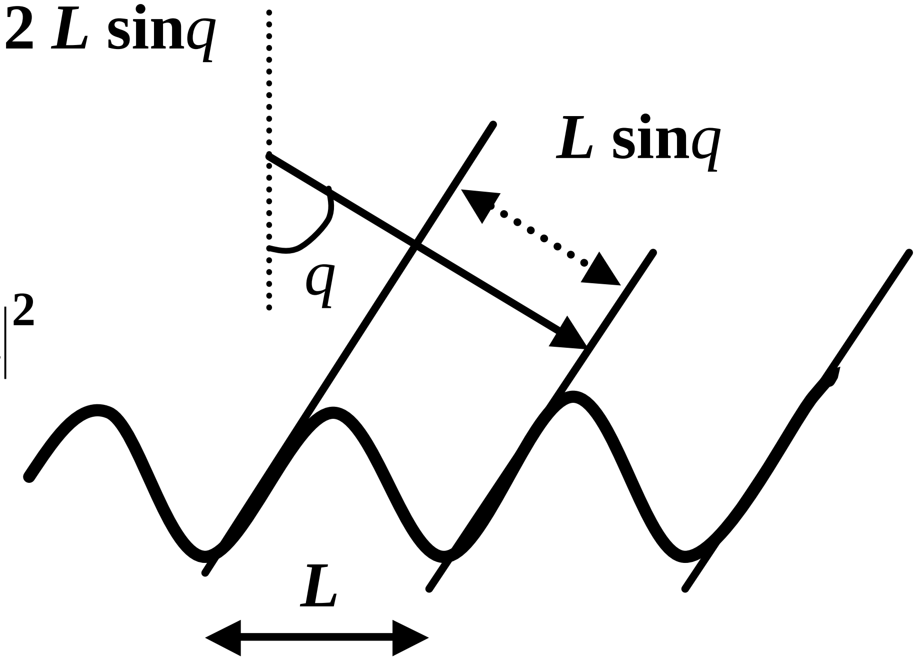
SAR Observation of Ocean Winds

- **How does a SAR image the ocean surface**
- **How are ocean winds estimated from SAR imagery**
- **Radar cross section models needed to estimate ocean winds**

Bragg Scattering

When the radar wavelength, l**, projected onto the surface matches a periodic structure on the surface, there is a resonance effect causing a strong backscatter => *bragg scattering***

$$l = 2\,L\,\sin q$$



(copied from Frank Monaldo, APL)

$$s_o = 8p\cos^4(q_i)\,S\left(2k\sin\left(q_i'\right), f\right)\left|R\right|^2$$

q_I **= radar incidence angle**
q_I**’ = local incidence angle of surface**
S(k,F**) = spectrum of surface**
k = radar wavenumber = 2p/l
F **= look direction of the radar**
R = reflectivity constant (depends on dielectric constant, q_I**)**

Bragg Scattering (cont.)

- **s_o is proportional to the amplitude of the "bragg wave" (the wave on the surface that matches the bragg condition) only**
  - **this is the only surface structure the radar "sees"**
- **Radar only "sees" the bragg waves that are moving toward or away from the sensor (moving in the F direction)**
- **A local tilting of the surface changes the local incidence angle q_I' and thus changes the wave on the surface that matches the bragg condition**

SAR Ocean Imaging

- **For SAR incidence angles between 20 and 60 degrees, *bragg scattering* is the dominant backscatter mechanism**
  - **for angles less than 20 degrees, specular scattering becomes dominant**

$$s_{\mathbf{o}} = \frac{p}{\mathbf{cos}^{4}(q_{\mathbf{i}})} |\mathbf{R_o}|^{2}\, \mathbf{exp}\left[- 4k^{2} s_{\mathbf{h}}^{2}\right] \mathbf{p}$$

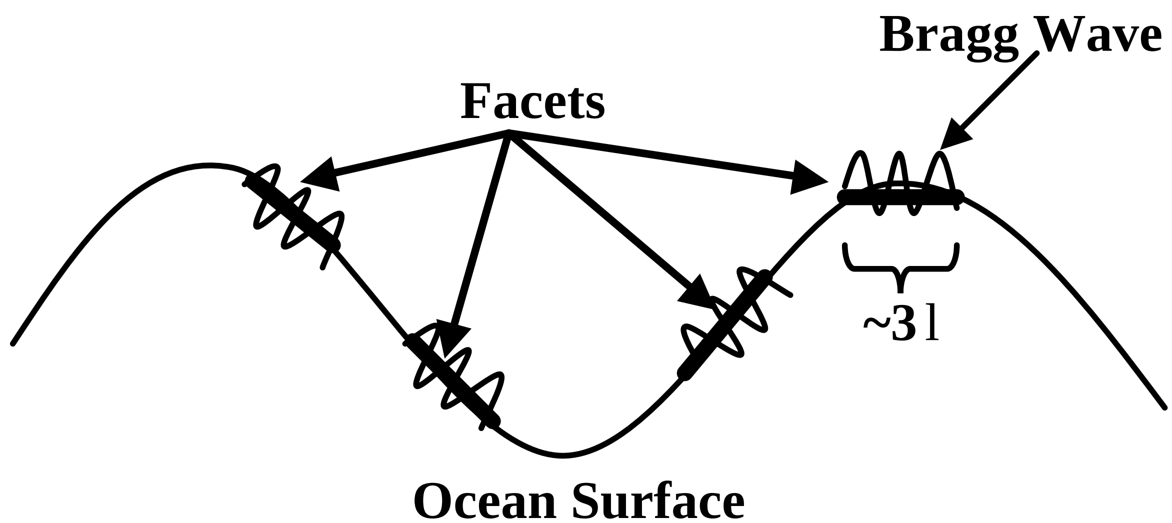
R_o = reflectivity for specular surface
s_h^2 = small-scale height variance
p = probability of a specular surface, q_i’ = tan(q_I)

  - **for angles greater than 60 degrees, no standard theory applies, but surface shape seems to become important**

SAR Ocean Imaging (cont.)

Two-Scale Model

Model the ocean surface as a set of flat facets. Each facet is ~3l in length. The radar cross section from each facet is determined by bragg scattering => determined by the amplitude of the bragg waves within the facet and the local tilt of the facet caused by large-scale waves



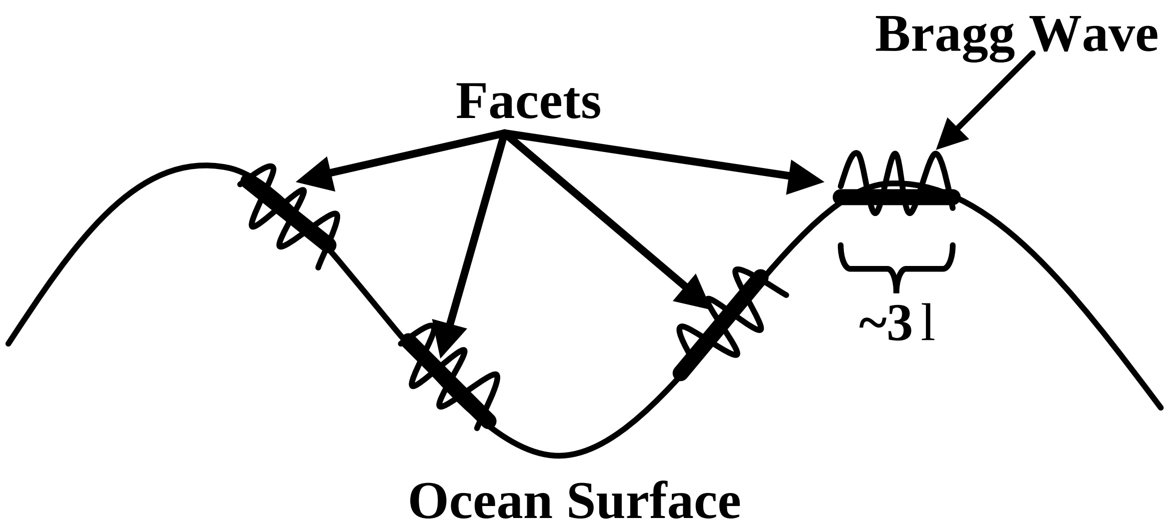
SAR Ocean Imaging (cont.)

Bragg waves are created by the local wind then propagate along the surface

=> amplitudes are determined by local wind conditions and ocean surface currents they encounter

Facet tilts are caused by the amplitudes of the long-scale waves

=> determined by local winds, swell

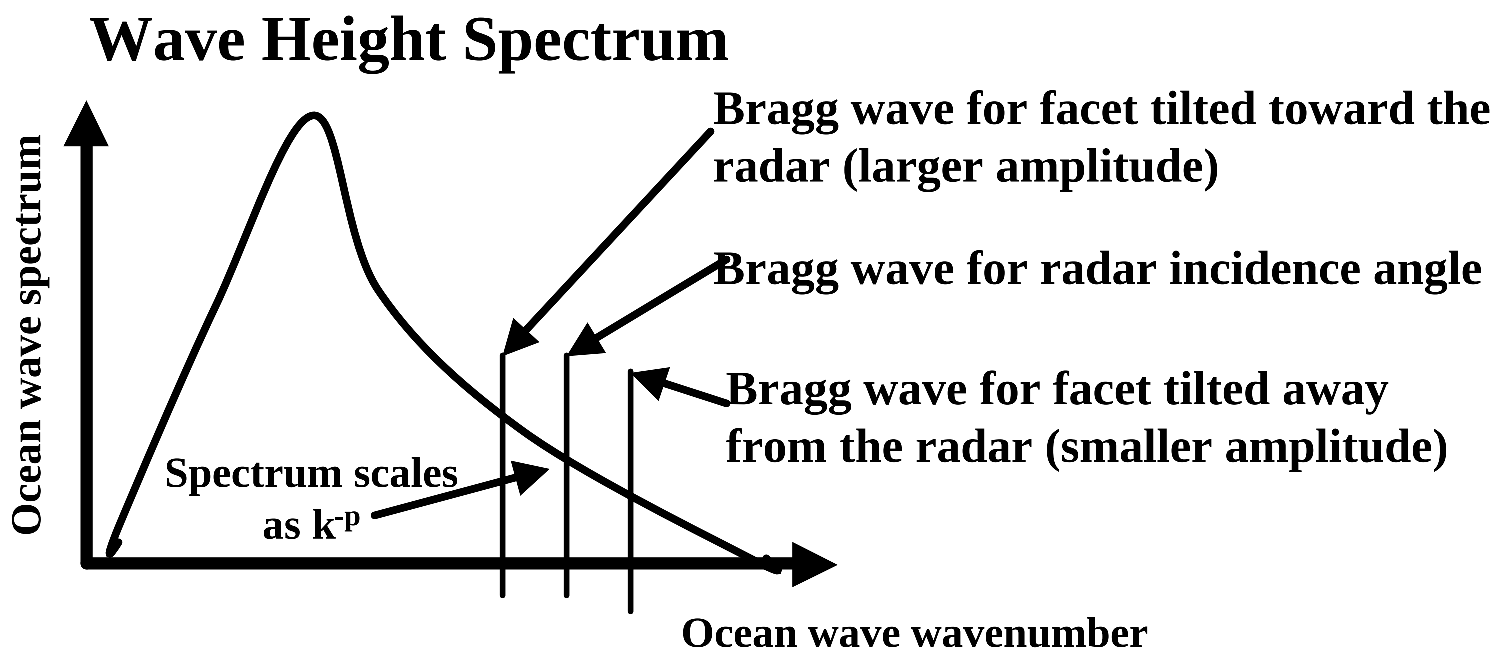


SAR Ocean Imaging (cont.)

- **SAR imaging of large-scale ocean structures (waves, fronts, surfactants, etc.) is <u>always</u> an indirect effect**
  - **SAR only sees the effect that the large-scale structures have on the bragg waves**
- **Ocean surface is always moving which causes image smearing**
  - **azimuth resolution of a SAR image of the ocean is (R/V)s_v where s_v is the standard deviation of bragg scatterer velocities within a facet (s_v ~ 0.2 to 0.4, R/V for an airplane ~ 50 - 80, R/V for a satellite ~ 110 - 150)**

SAR Ocean Imaging (cont.)

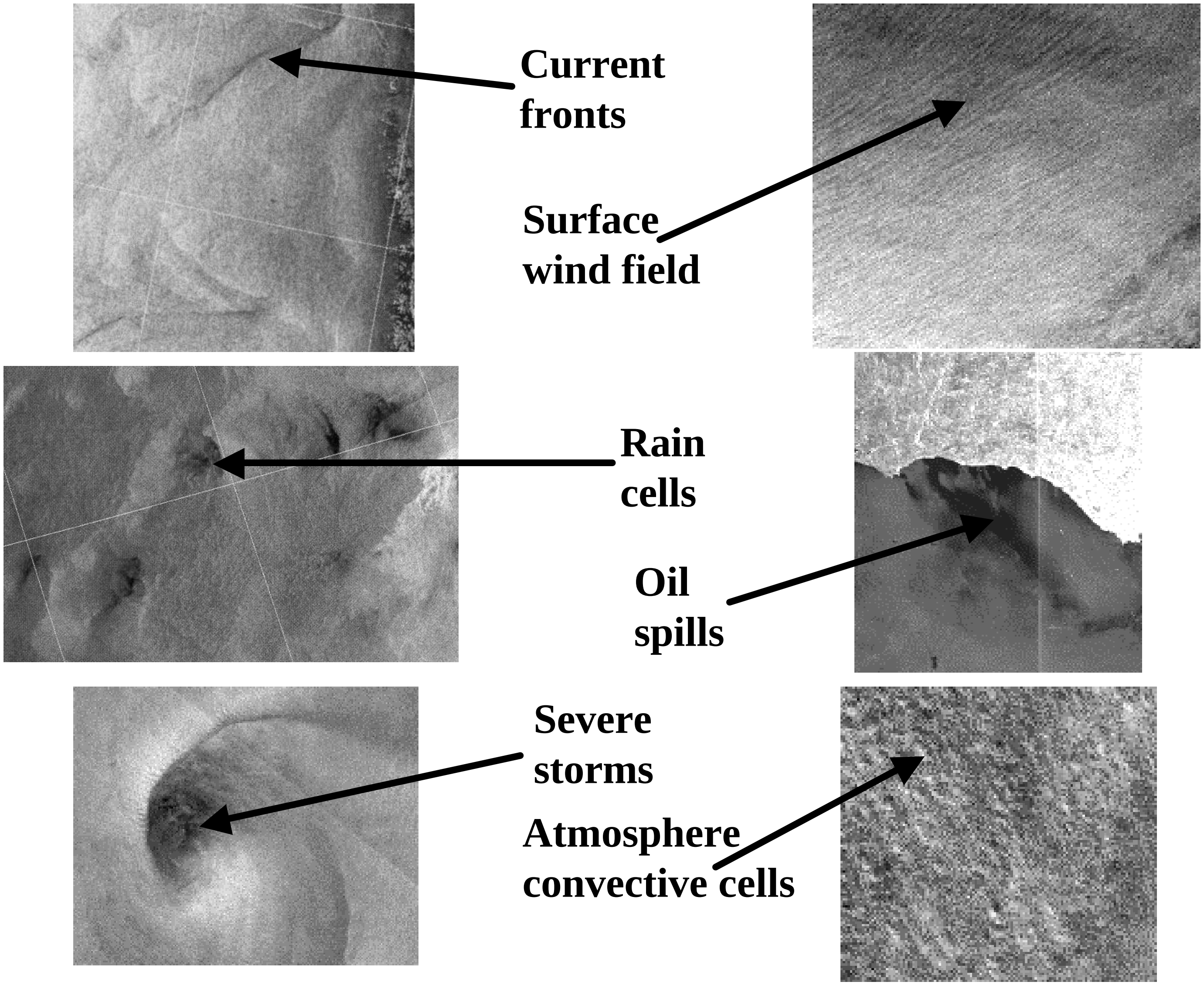
Tilting the facet changes the amplitude of the bragg wave because the wave height spectrum is not flat around the bragg wave location => knowing the spectrum in this bragg region is very important to SAR ocean imaging (models range from k^{-4} to k^{-8})



How Does A SAR Image ...

- **large-scale waves**
  - orbital velocities induce currents on the surface that affect the bragg wave amplitudes, local surface slope tilts the local facets
- **current fronts**
  - bragg wave amplitudes are affected as they cross the current front, bragg waves are refracted
- **oil spills, surfactents**
  - dampens the ocean surface, removing all bragg waves => no backscatter
- **local wind**
  - wind speed/direction changes bragg wave amplitude
- **internal waves**
  - wave propagation caused modulation of surface currents, the bragg waves pass through these currents and change their amplitudes
- **bathymetry**
  - flow over the bathemetric feature (usually tidal flow) causes modulation of surface currents, the bragg waves pass through these currents and change their amplitudes
- **atmospheric conditions**
  - local changes in wind speed/direction change bragg wave amplitudes

Example SAR Signatures From Various Events



SAR Observation of Ocean Winds

Based on two-scale Bragg scattering, s_o from wind generated waves will depend on:

(1) wind speed

faster wind => higher s_o

(2) wind direction

Higher s_o when looking into/away from the wind, lower when looking cross wind

(3) local incidence angle

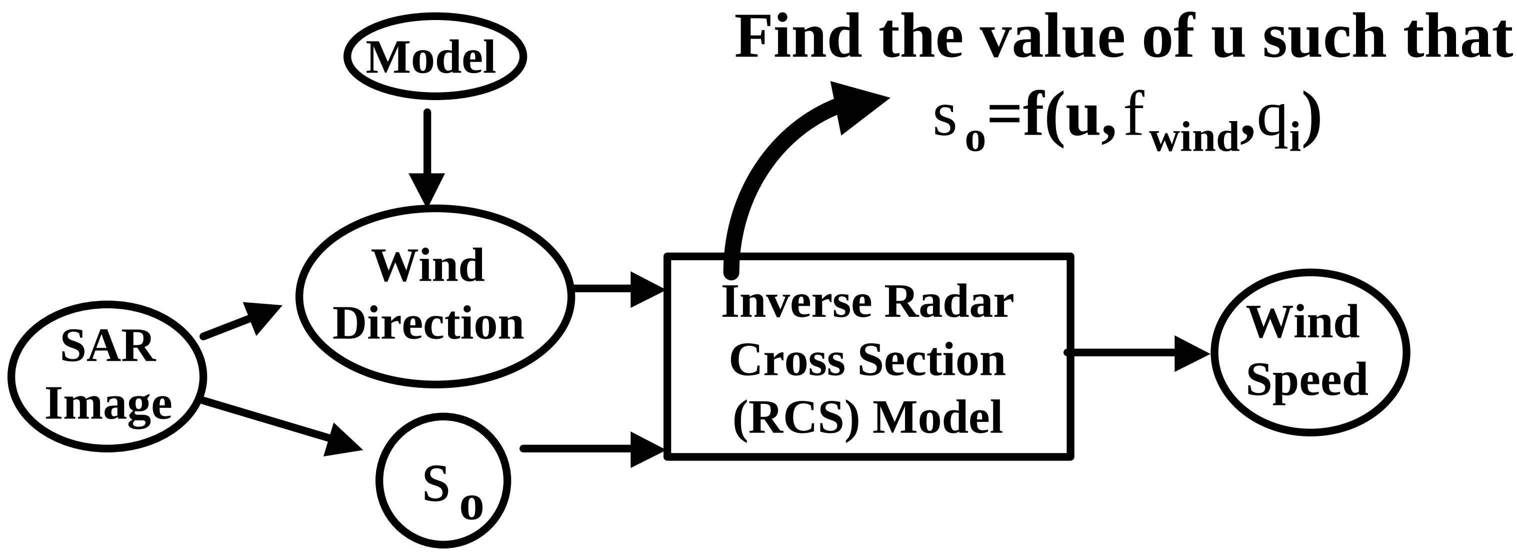
Higher s_o for high incidence angle

=> can develop a RCS model s_o=f(u,f_{wind},q_i)

(u = wind speed, f_{wind} = wind direction with respect to the SAR look direction, q_i = incidence angle)

Models have been developed for C-VV (CMOD4), but no standard model exists for C-HH

Estimating Ocean Winds From SAR Imagery



AKDEMO needed to develop the C-HH RADARSAT RCS model to perform the inversion

- **Modifications of CMOD4 C-VV model**
- **New model for C-HH**

C-HH RCS Models Examined

(1) Two Scale Model

$$\sigma_o^H = \iint \sigma_b(s_u, s_c)\left[1 + s(u)h(s_u, s_c)\right]\rho(s_u, s_c)\,ds_u\,ds_c$$

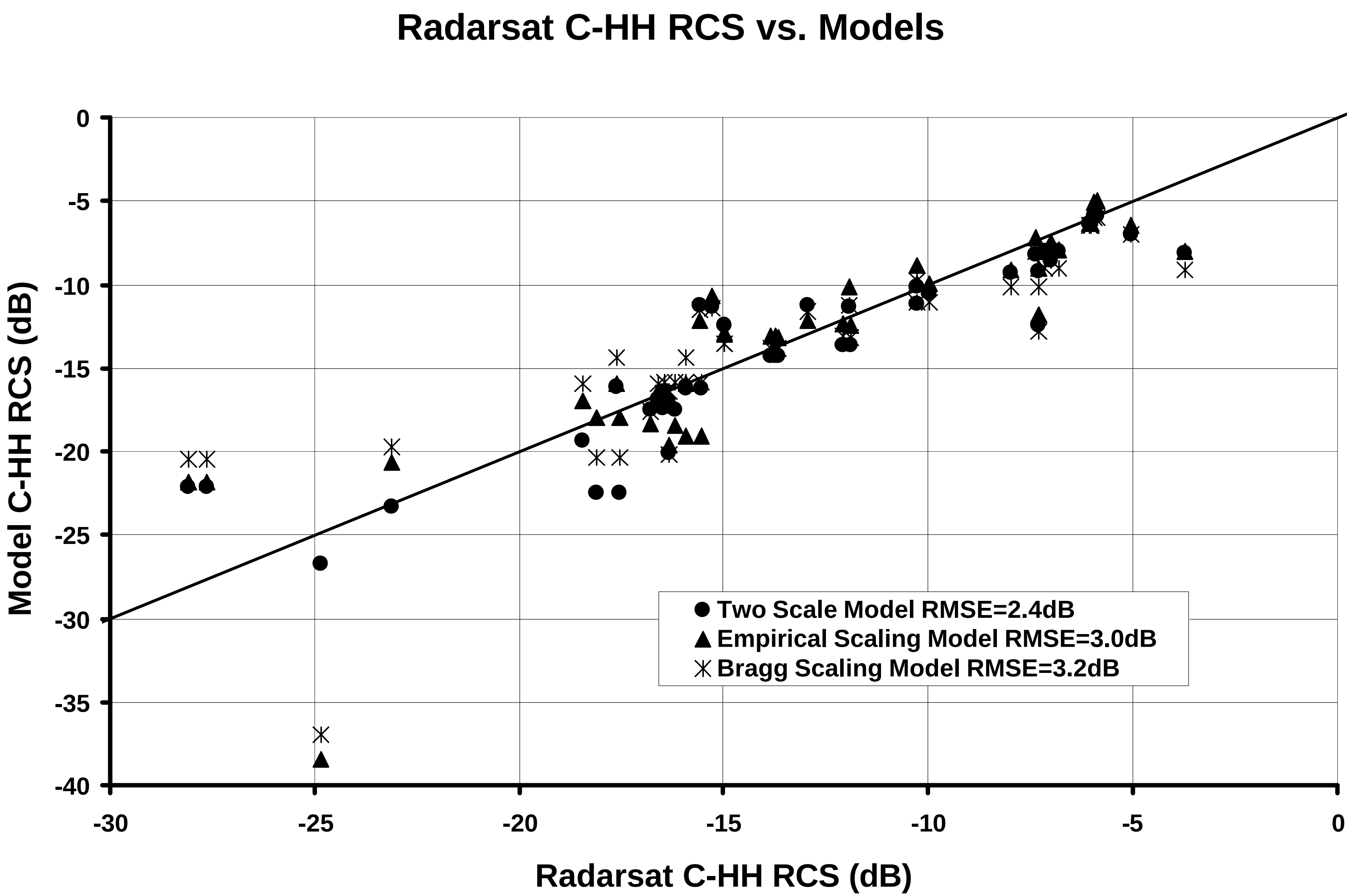
$$s(u) = a_3u^3 + a_2u^2 + a_1u + a_0$$

(2) Empirical Scaling Model

$$\sigma_o^H = \sigma_o^V\left(a_3\tan^3\theta_i + a_2\tan^2\theta_i + a_1\tan\theta_i + a_0\right)$$

(3) Bragg Scaling Model

$$\sigma_o^H = \sigma_o^V\frac{\left(1 + a_0\tan^2\theta_i\right)^2}{\left(1 + 2\tan^2\theta_i\right)^2}$$


Radarsat C-HH RCS vs. Models
Model C-HH RCS (dB)
0
-5
-10
-15
-20
-25
-30
-35
-40
-30
-25
-20
-15
-10
-5
0
Radarsat C-HH RCS (dB)
Two Scale Model RMSE=2.4dB
Empirical Scaling Model RMSE=3.0dB
Bragg Scaling Model RMSE=3.2dB

Alaska SAR Demonstration Wind Vector Products

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Wind Vector Products Presentation

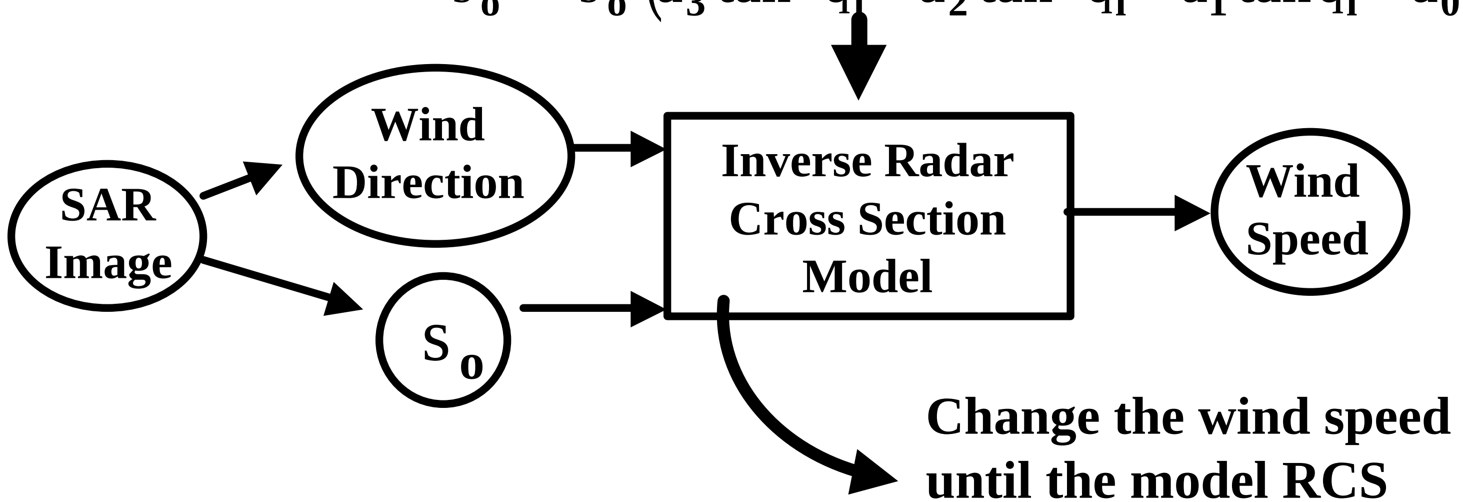
- Description of wind vector algorithm
- Example image products
- Algorithm performance
- Future Work

Estimating Ocean Winds From SAR Imagery

$$\sigma_{\mathbf{o}}^{\mathbf{H}} = \iint \sigma_{\mathbf{b}}(\mathbf{s_u},\mathbf{s_c})[\mathbf{1}+\mathbf{s(u)h}(\mathbf{s_u},\mathbf{s_c})]\rho(\mathbf{s_u},\mathbf{s_c})\mathbf{ds_u ds_c}$$

or

$$\sigma_{\mathbf{o}}^{\mathbf{H}} = \sigma_{\mathbf{o}}^{\mathbf{V}}\left(\mathbf{a_3 \tan^3}\theta_{\mathbf{i}} + \mathbf{a_2 \tan^2}\theta_{\mathbf{i}} + \mathbf{a_1 \tan}\theta_{\mathbf{i}} + \mathbf{a_0}\right)$$

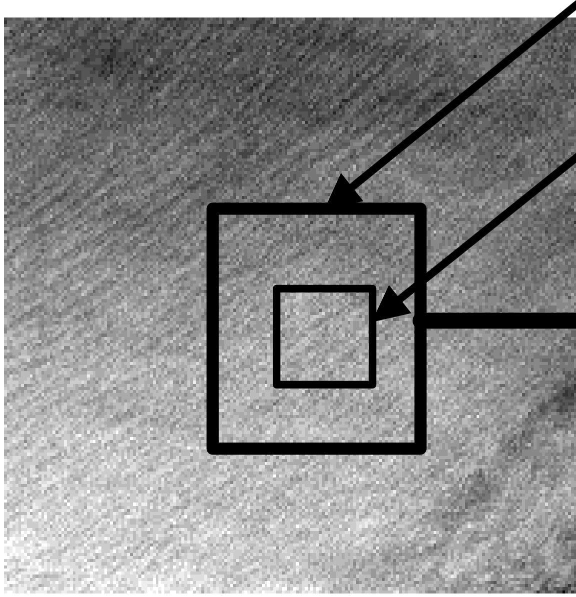


Change the wind speed until the model RCS matches the RCS in the image

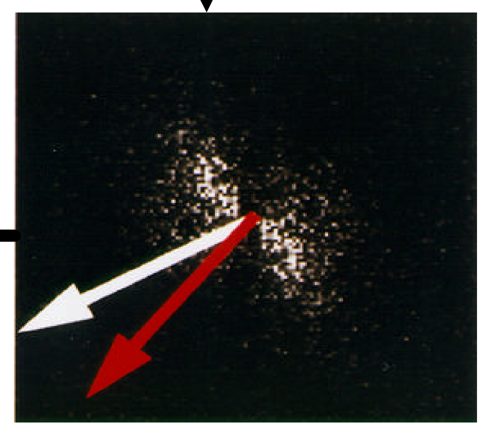
Estimating Wind Direction From SAR

Region to use to estimate a wind vector

Region to use to generate a spectrum from the image



Form a smoothed spectrum by calculating a spectrum over multiple placements of the smaller region, then averaging the spectra



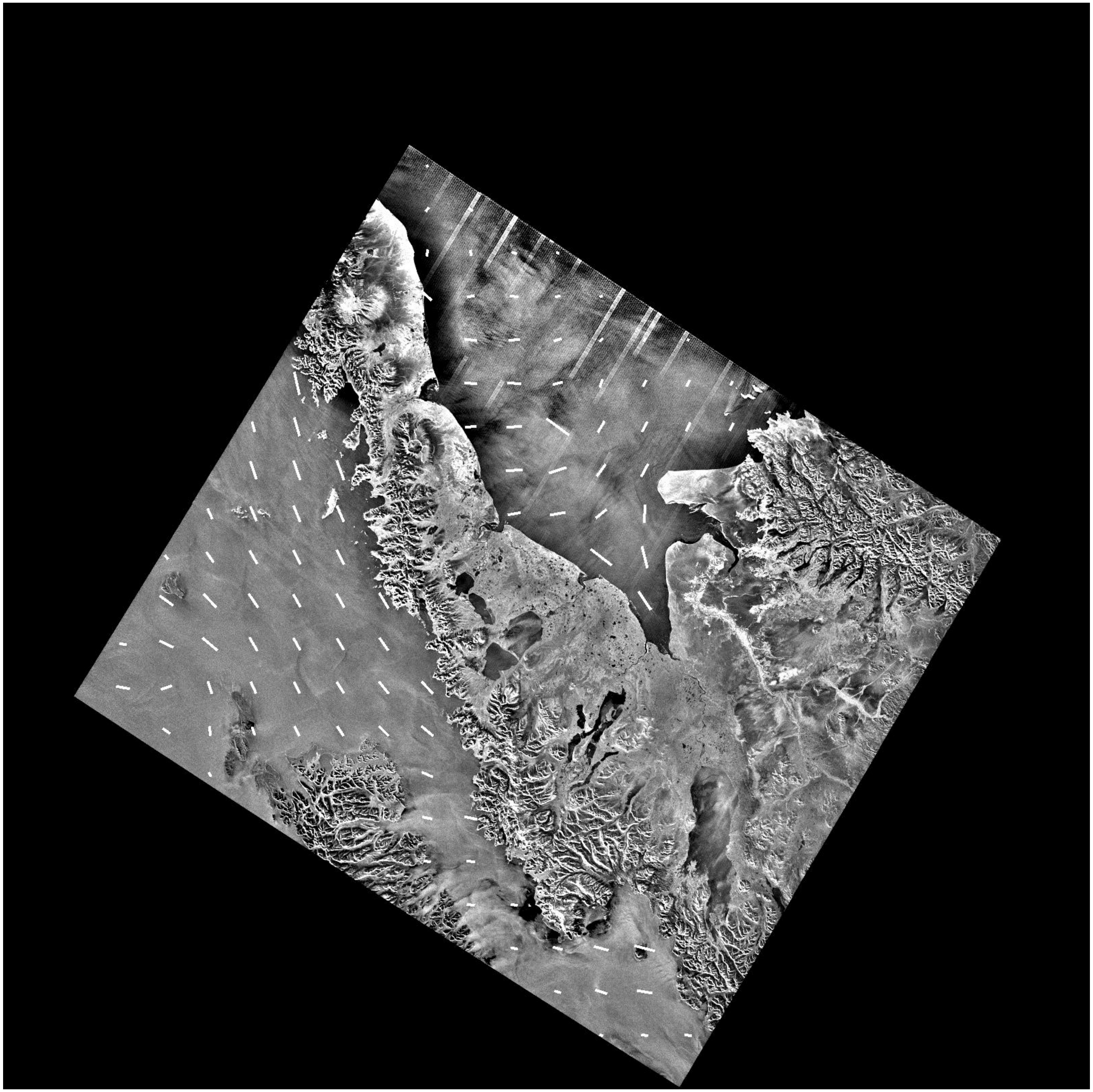
Calculate the elongation direction of the spectral energy over large scales (3 - 20 km), wind direction is rotated 90 degrees from this direction (red=estimate, white=actual)

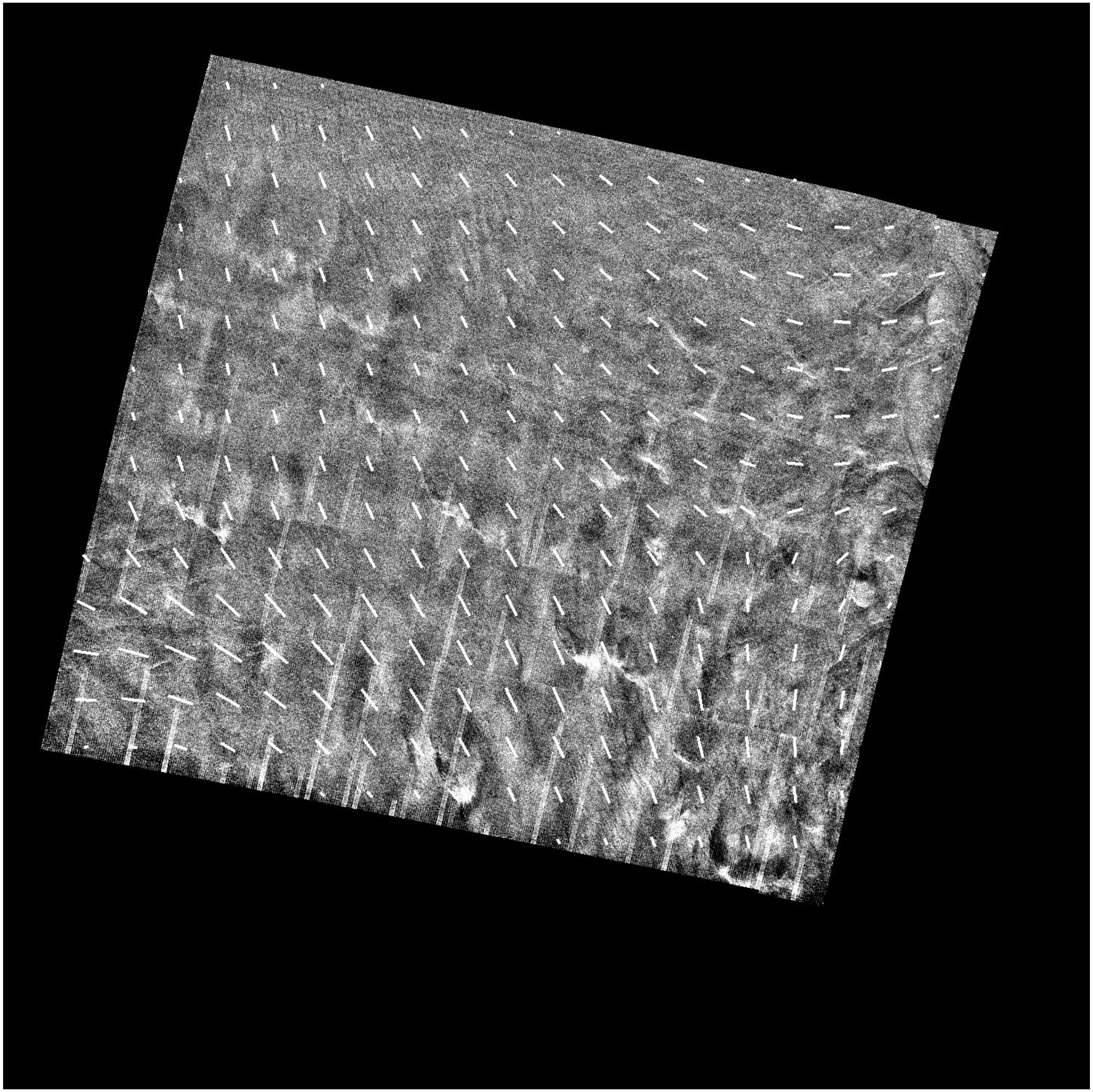
Estimating Wind Direction From SAR (cont.)

- **Wind direction estimates have a 180 degree ambiguity**
- **Direction of large-scale spectrum elongation is estimated by fitting a quadratic polynomial to the low wavenumber portion of the spectrum**
- **Land is masked out using a coastline map**
  - **2 km uncertainty is added for registration errors**
- **Smooth wind directions using a 3x3 weighted average with the RCS values as the weights**

Final Wind Algorithm Products

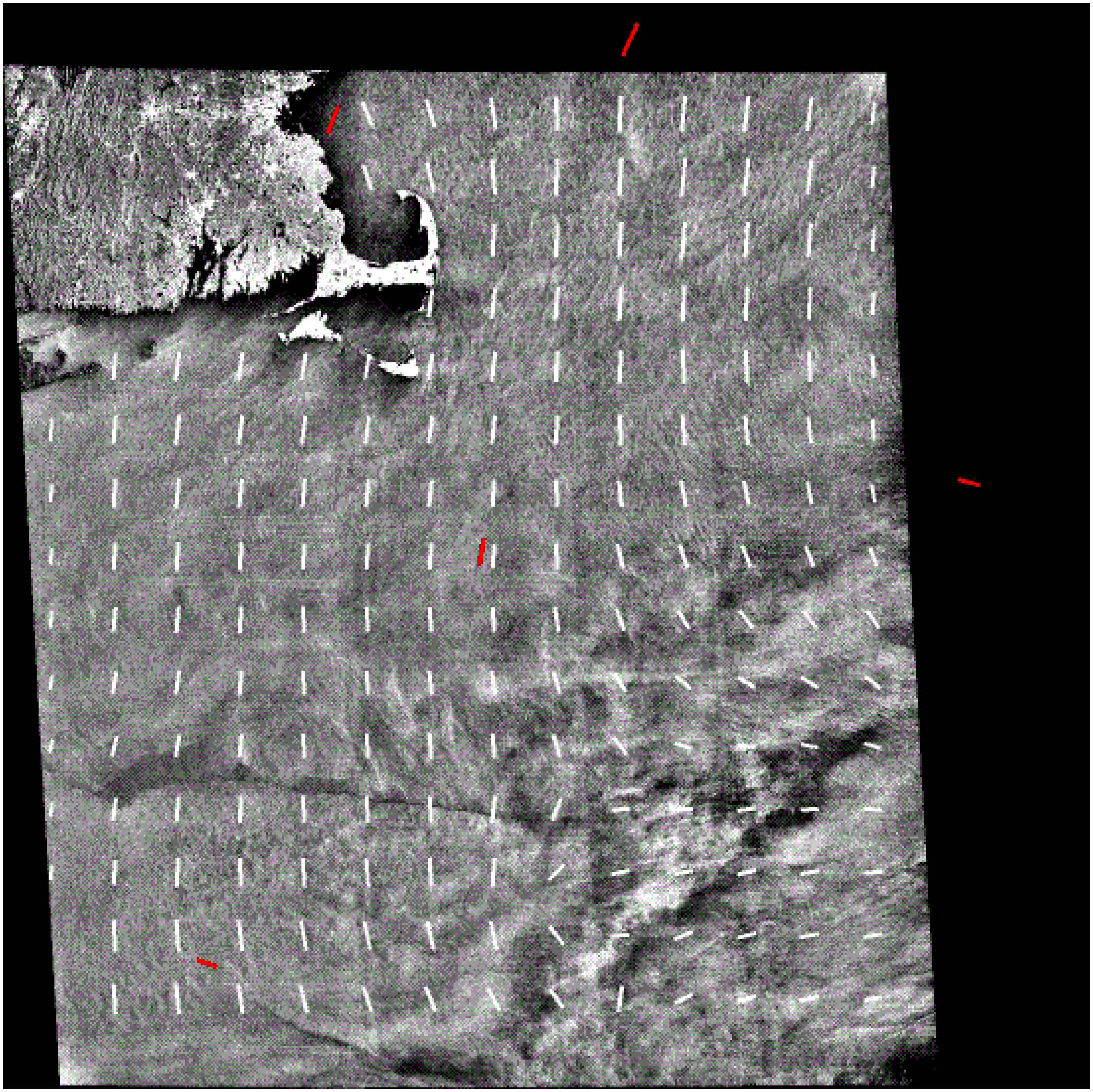
- **Combine wind direction estimate with averaged RCS to generate wind speed**
- **Generate an ascii file of latitude / longitude locations with wind speed and direction**
  - **remember 180 deg ambiguity with wind direction**
- **Generate a graphic of the RADARSAT image with wind vectors superimposed over the image**
  - **vectors have no “head” due to ambiguity**

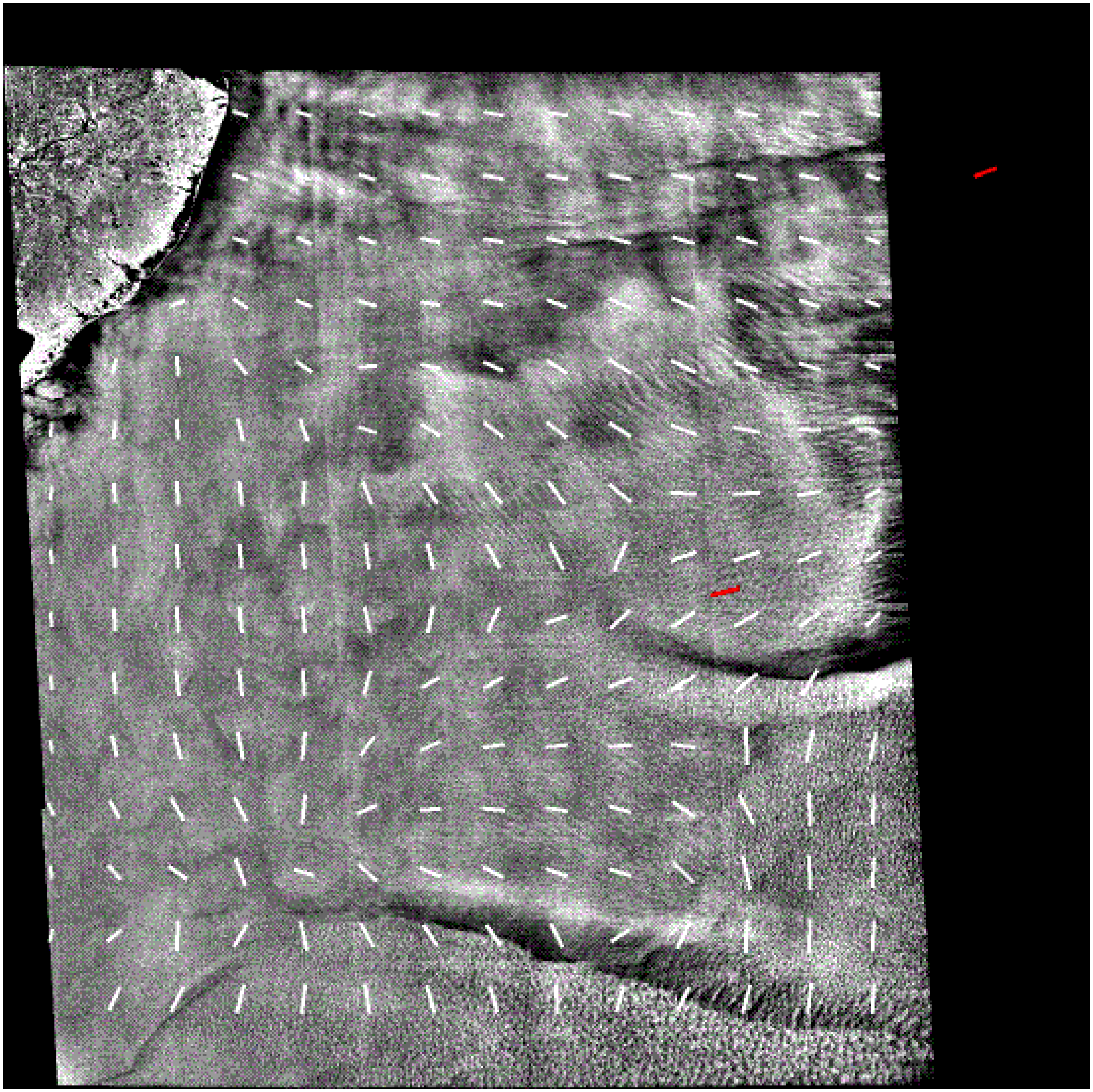


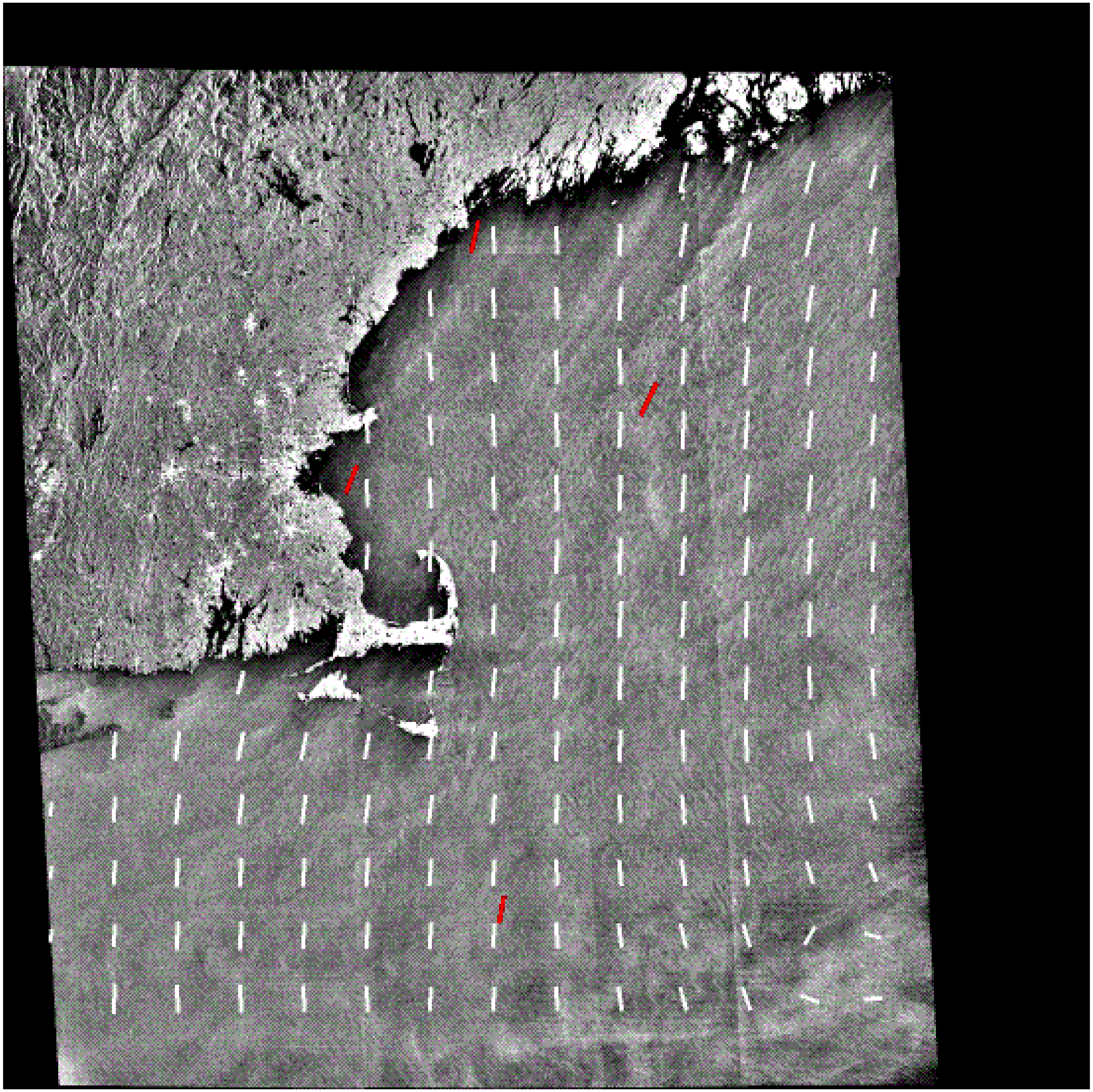


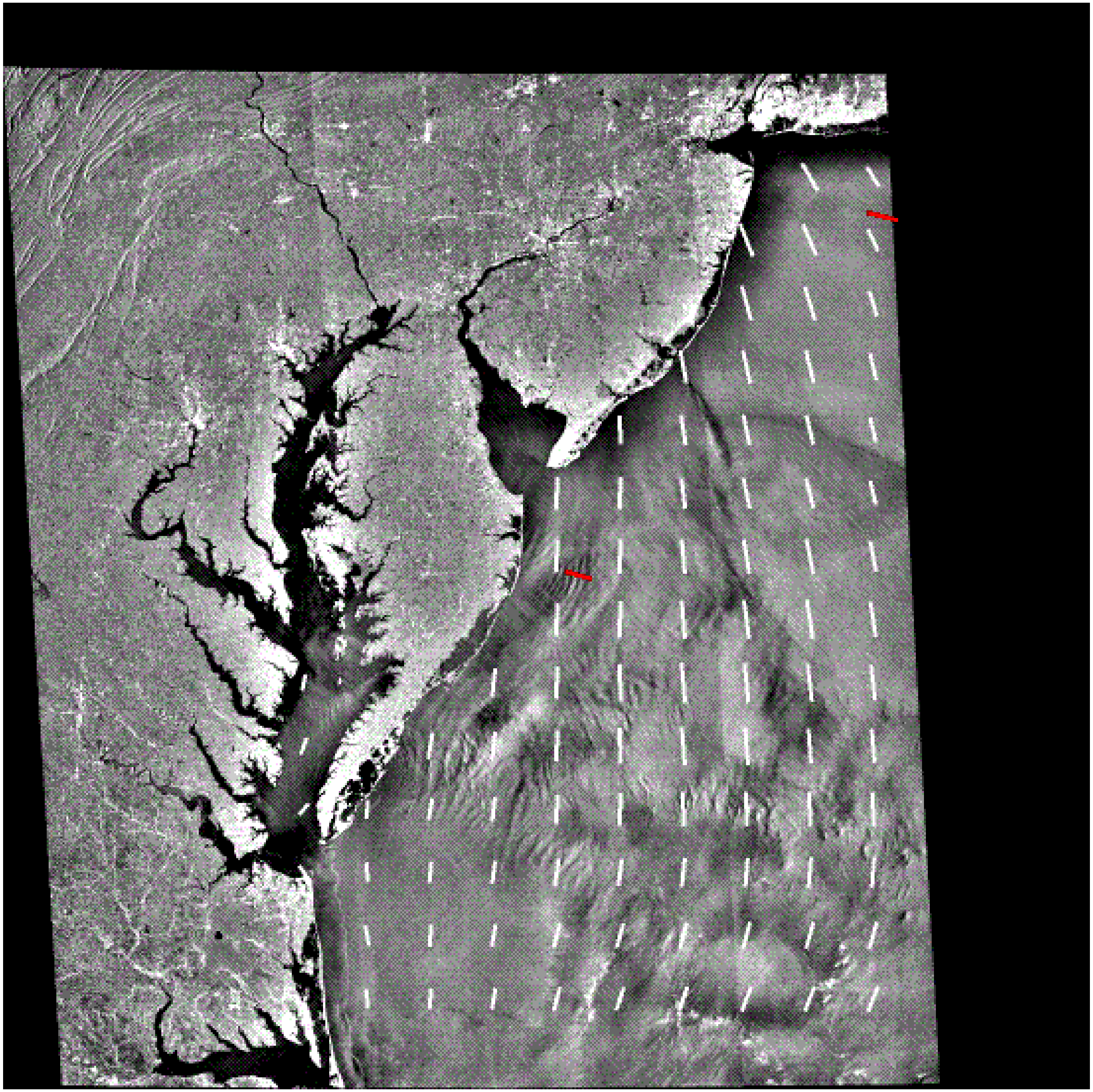
Estimating Wind Algorithm Performance

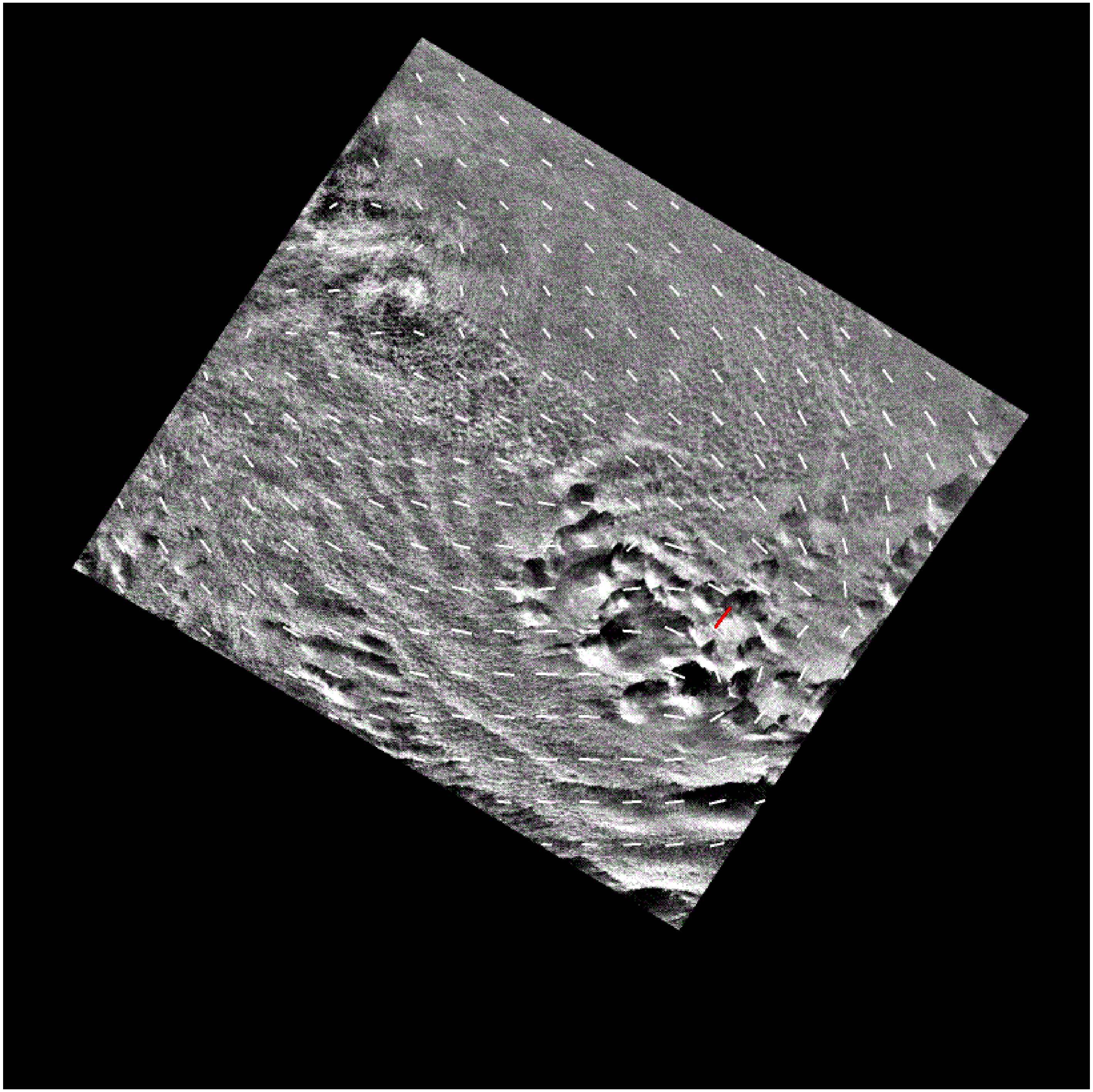
- **Series of RADARSAT imagery was collected off the east coast of the U.S. containing NOAA buoys**
- **Wind speed, direction from the buoys were used as ground truth**
- **Nearest estimated wind vector from the image was used to compare to the buoy data**
- ***In following images, white lines are estimated vectors, red lines are buoy-derived vectors***

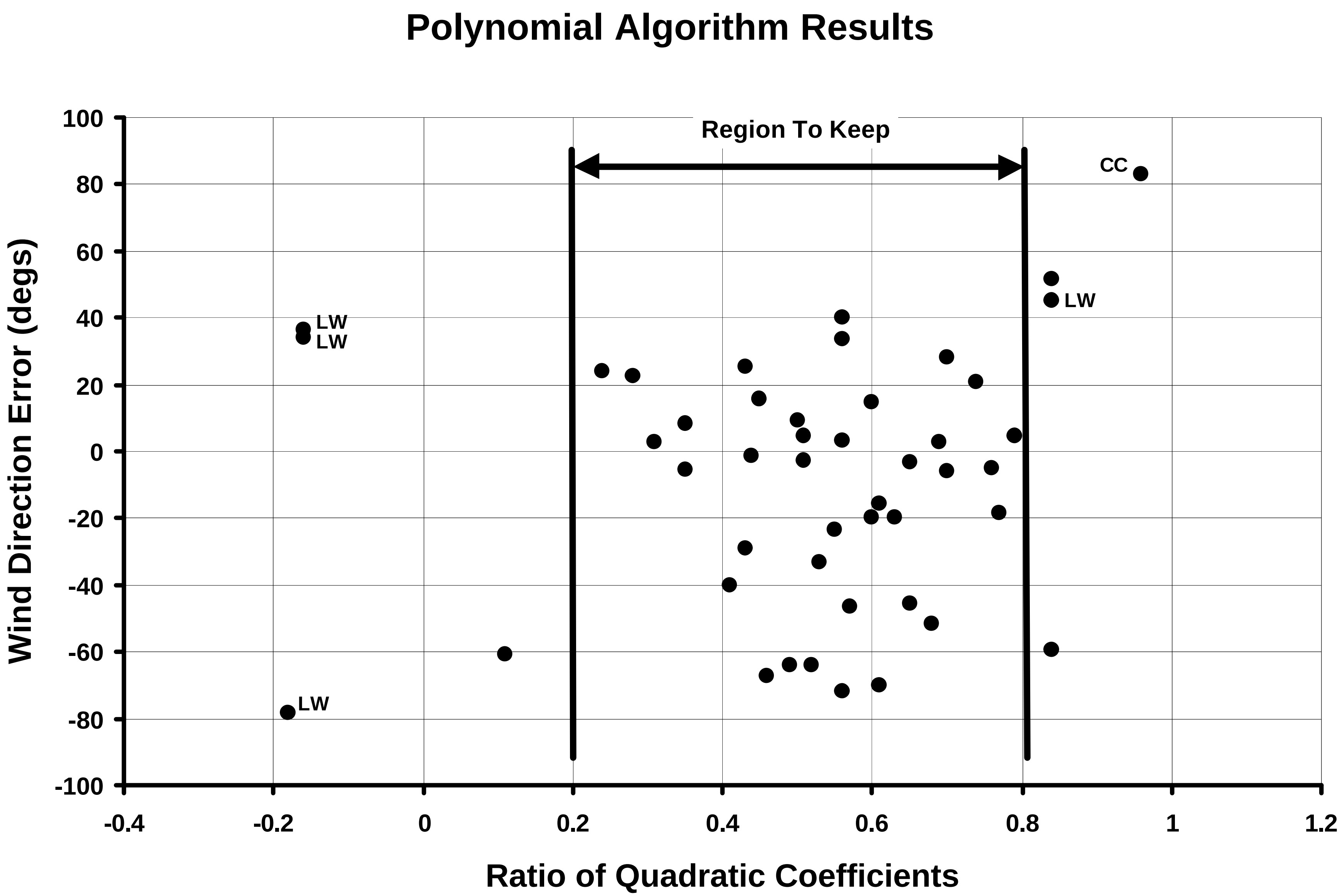


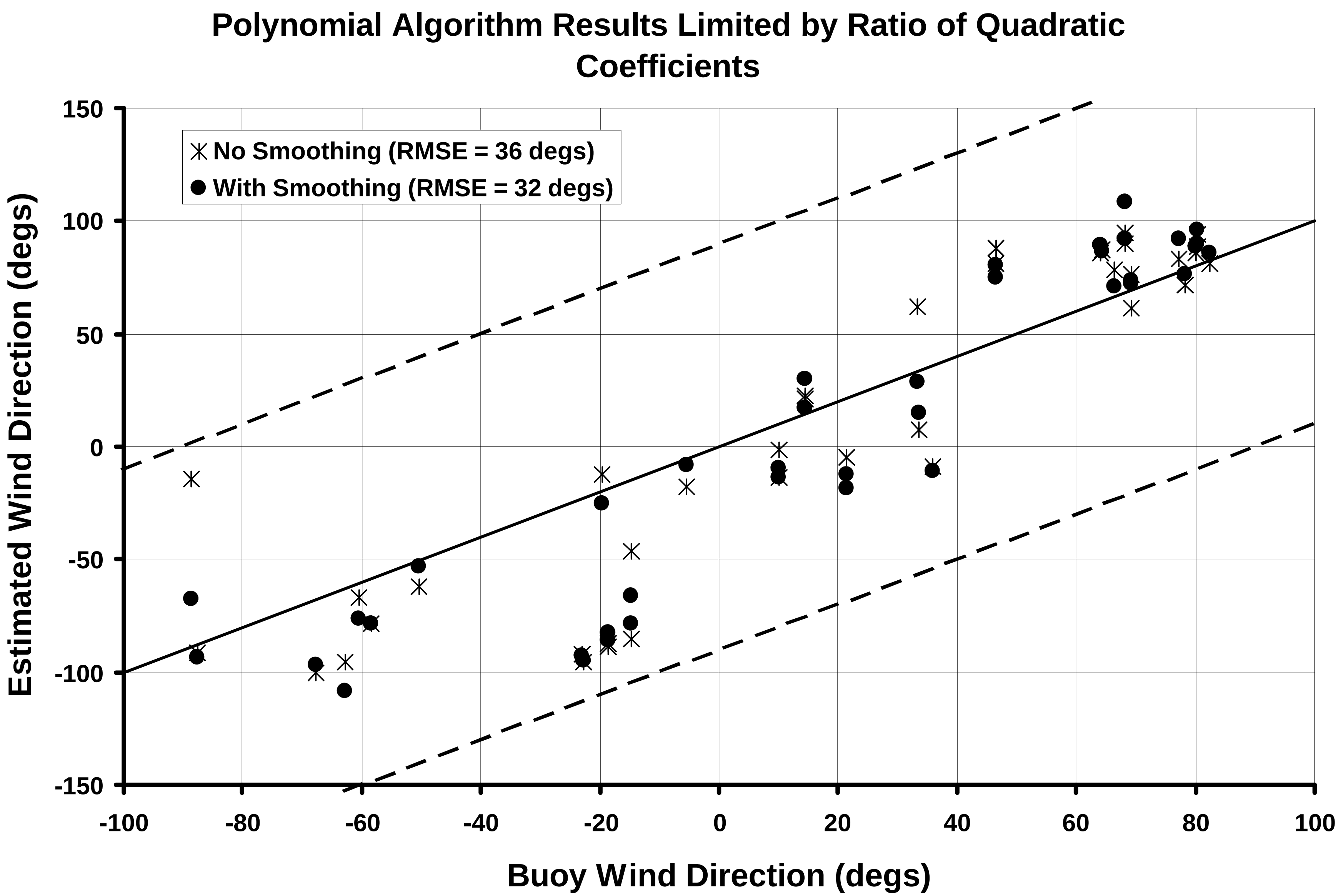


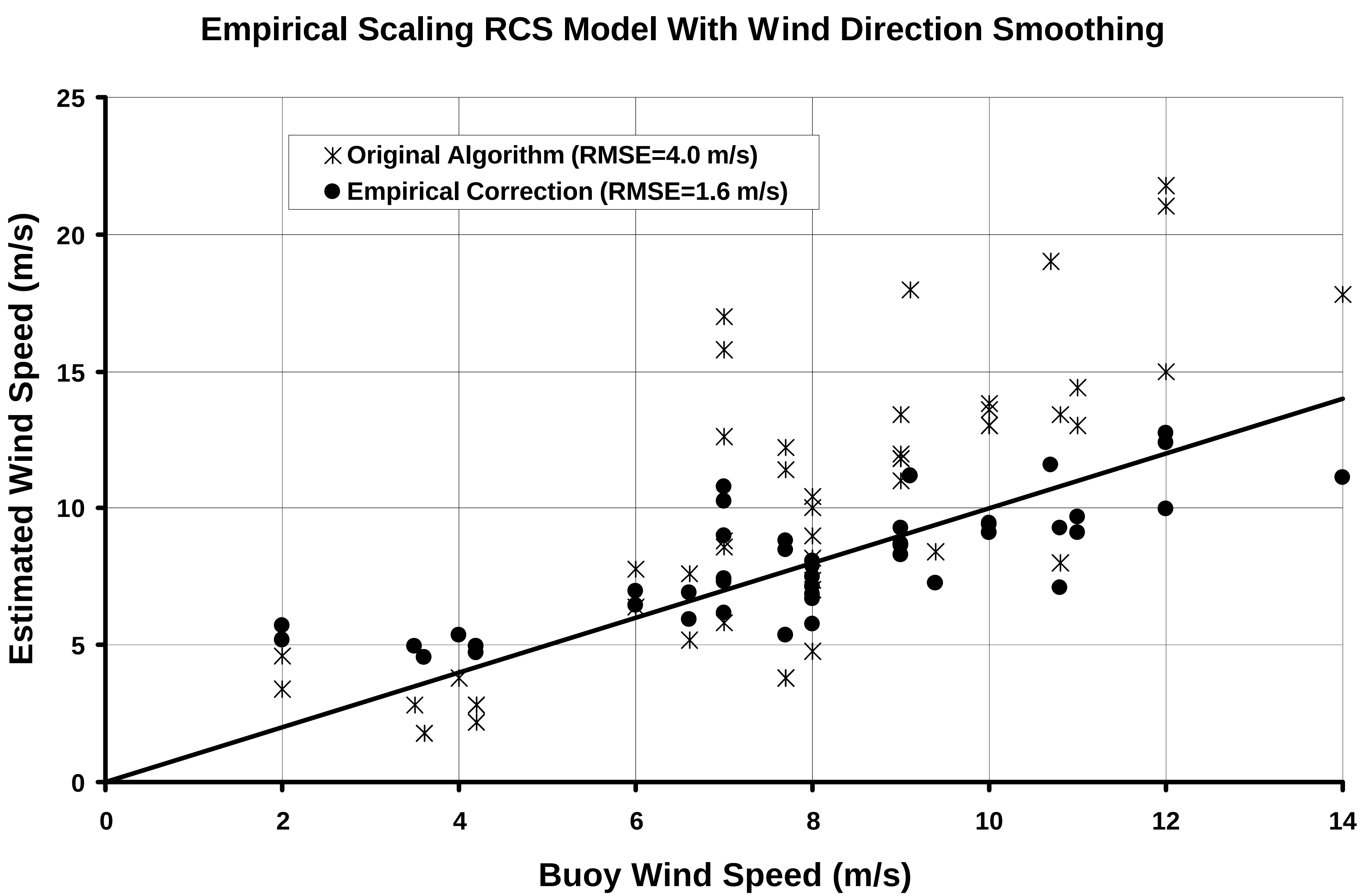


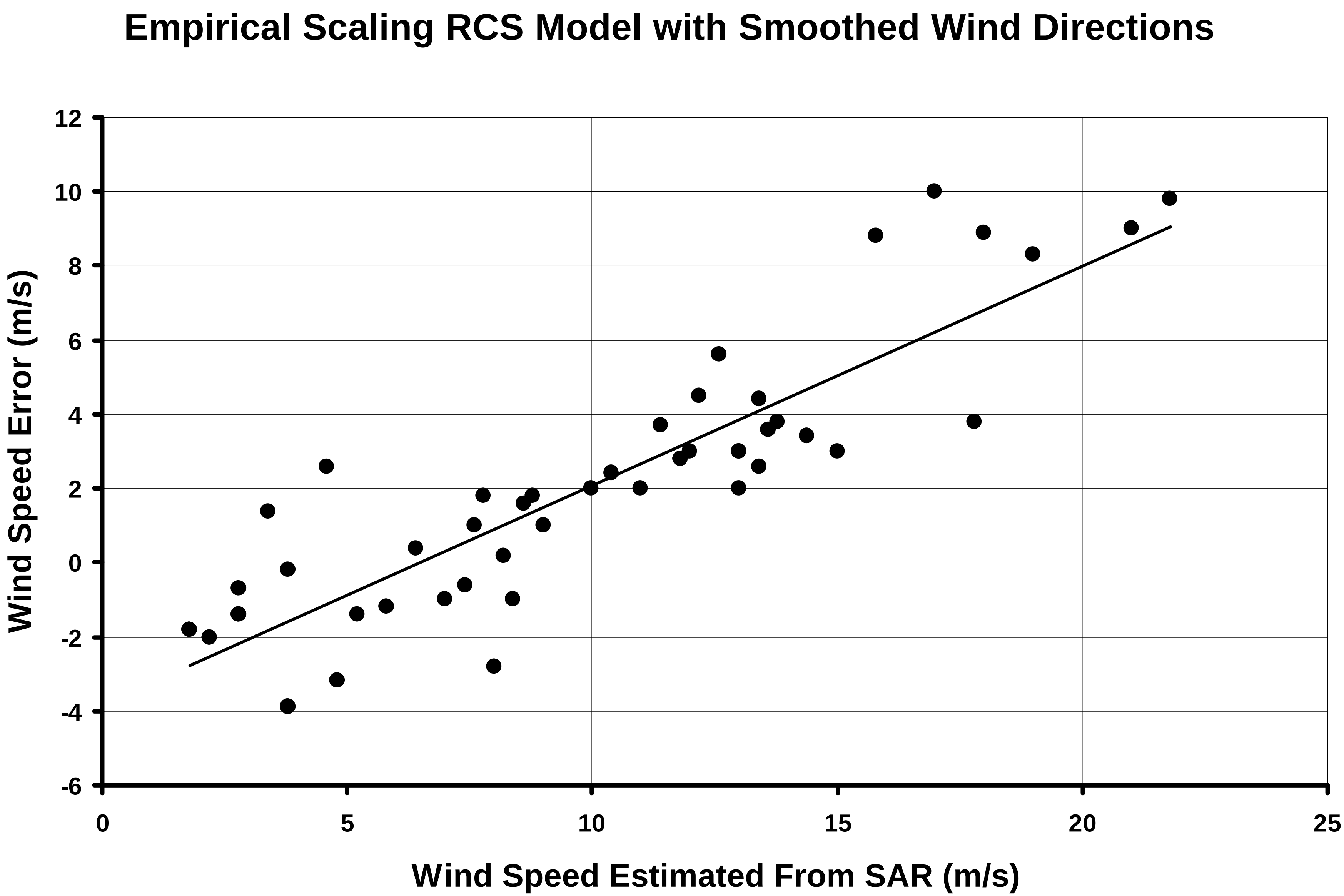





Polynomial Algorithm Results
Region To Keep
CC
LW
LW
LW
LW
LW
Wind Direction Error (degs)
100
80
60
40
20
0
-20
-40
-60
-80
-100
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
1.2
Ratio of Quadratic Coefficients


Polynomial Algorithm Results Limited by Ratio of Quadratic Coefficients
No Smoothing (RMSE = 36 degs)
With Smoothing (RMSE = 32 degs)
Estimated Wind Direction (degs)
Buoy Wind Direction (degs)
150
100
50
0
-50
-100
-150
-100
-80
-60
-40
-20
0
20
40
60
80
100


Empirical Scaling RCS Model With Wind Direction Smoothing
Original Algorithm (RMSE=4.0 m/s)
Empirical Correction (RMSE=1.6 m/s)
Estimated Wind Speed (m/s)
Buoy Wind Speed (m/s)
0
5
10
15
20
25
0
2
4
6
8
10
12
14

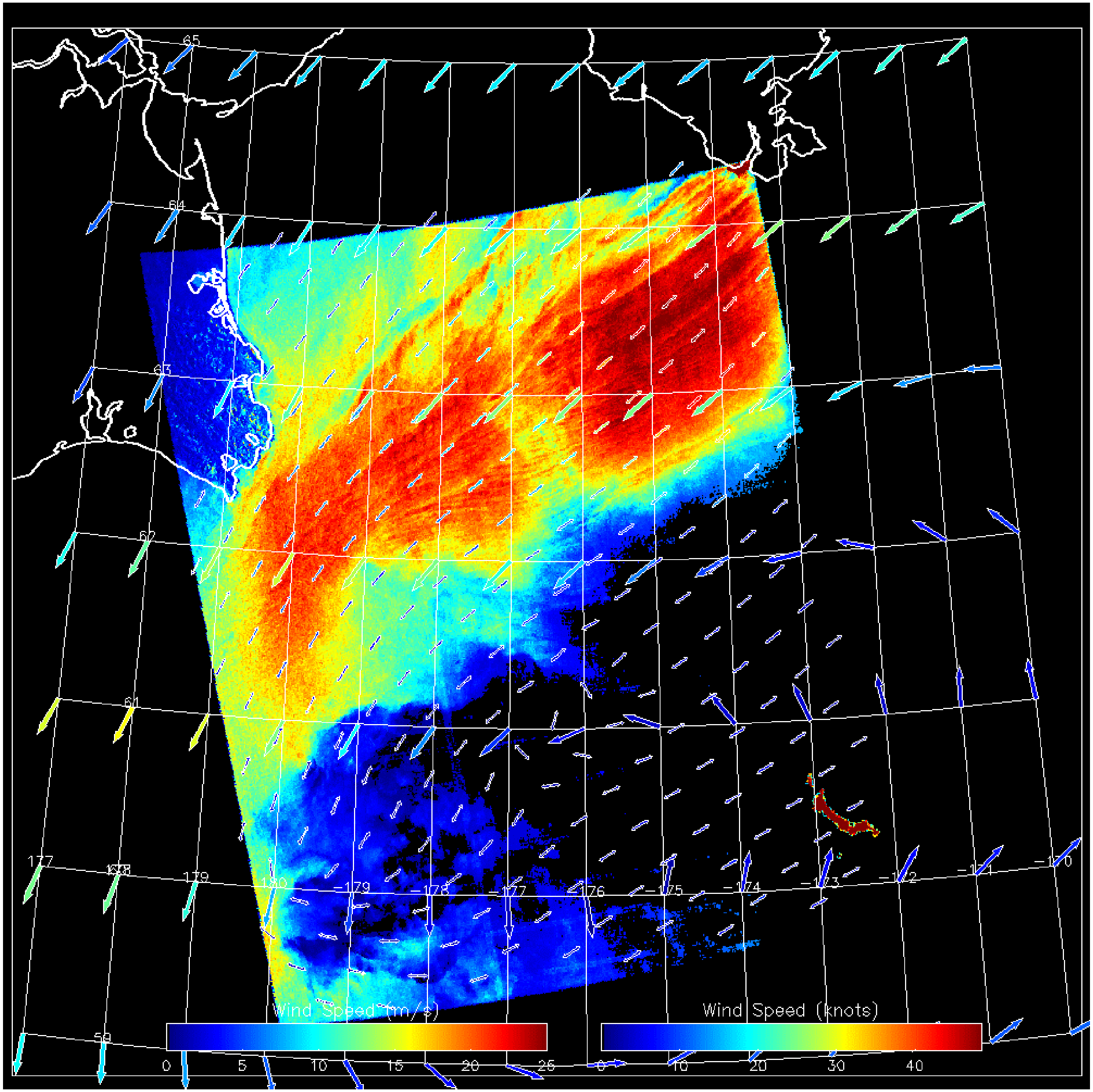

Empirical Scaling RCS Model with Smoothed Wind Directions
Wind Speed Error (m/s)
12
10
8
6
4
2
0
-2
-4
-6
0
5
10
15
20
25
Wind Speed Estimated From SAR (m/s)

Wind Algorithm Performance

- Wind direction errors:
  - over the entire data set: RMSE = 41 degs
  - after checking for adequate ratio of quadratic coefficients: RMSE = 36 degs
  - after applying spatial smoothing: RMSE = 32 degs
- Wind speed errors:
  - RMSE = 4.0 m/s without mean bias removed
  - RMSE = 1.6 m/s with mean bias removed

Wind Algorithm Future Work

- **More robust metric for when to believe direction estimate from the SAR image**
  - **procedure to replace the direction from surrounding estimates or model outputs**
- **Merging of the two algorithms from the two contractors into a single AKDEMO algorithm**



Wind Speed (m/s)
0 5 10 15 20 25
Wind Speed (knots)
0 10 20 30 40

Alaska SAR Demonstration Vessel Detection Products

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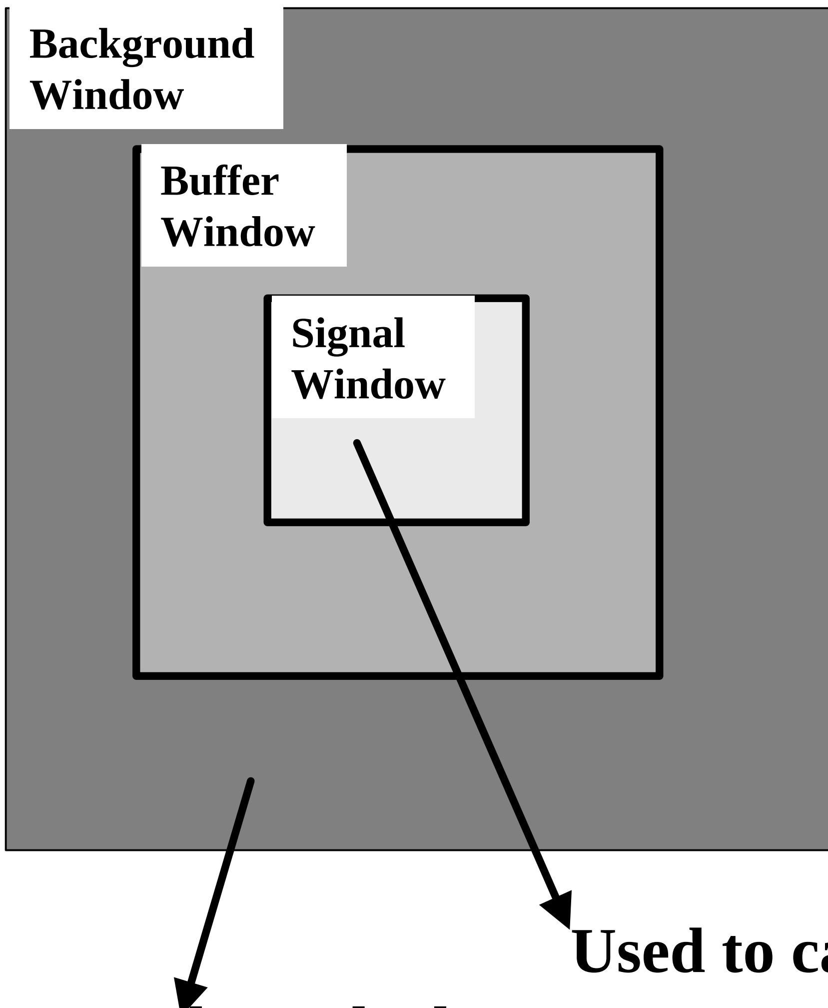
Vessel Detection Products Presentation

- Description of automated detection algorithm
- Example graphical products
- Algorithm performance estimation
- Future work

Nested Windows Used in the Ship Detection Algorithm



For each placement of the set of local windows, calculate a detection statistic, d:

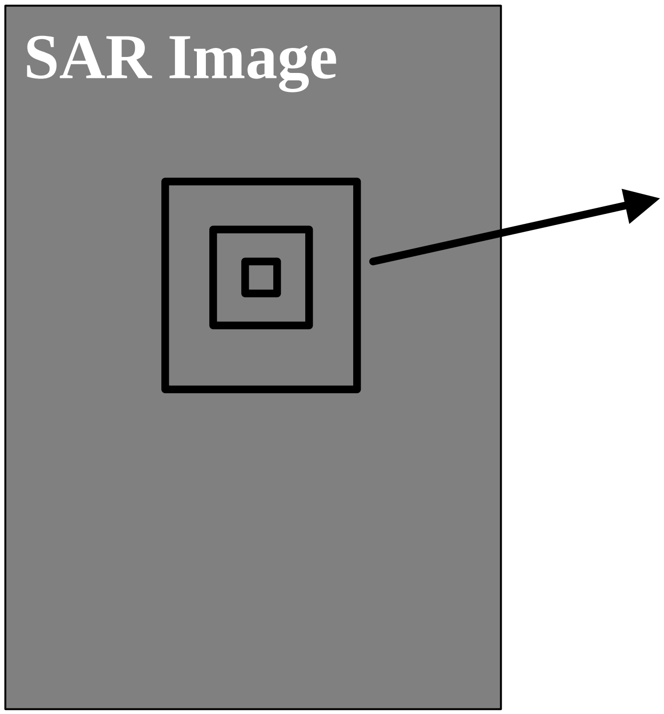
$$d = \frac{(m_s - m_b)}{s_b}$$

d is a CFAR statistic: constant false alarm rate

Used to calculate m_s

Used to calculate m_b, s_b

Vessel Detection Algorithm



For each placement of the local windows, a vessel is detected if:

$d > T_o = 5.5$ in water regions

$= 12$ in noise regions

$m_s > m_o = .03$

$m_b < m_1$ (varies for each image)

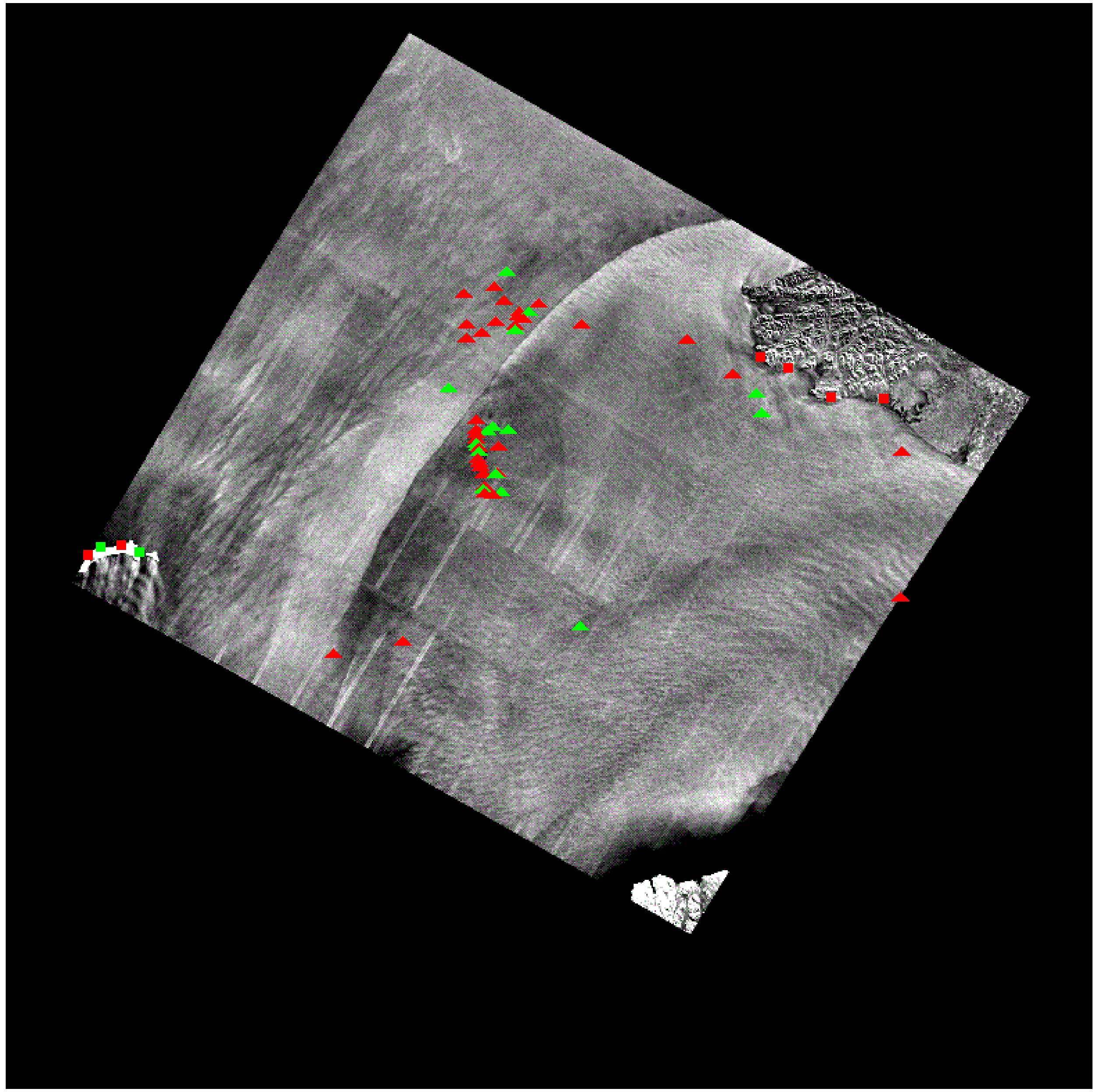
$s_b < s_1 = 0.003$ (near land)

Detections are ignored if there are more than 2 km from water, but kept if they are within 2 km of shore in order to handle possible registration errors.

Vessel Detection Algorithm

- Statistics are calculated using a "fast" algorithm that just continually adds and subtracts from sums over window samples
- Approach allows a Wide Swath ScanSAR image to be processed in approximately 10 minutes of elapsed time.
- Output products:
  - ascii file of ship locations (latitude,longitude) and ancillary information
  - graphical product of ship locations superimposed on RADARSAT image

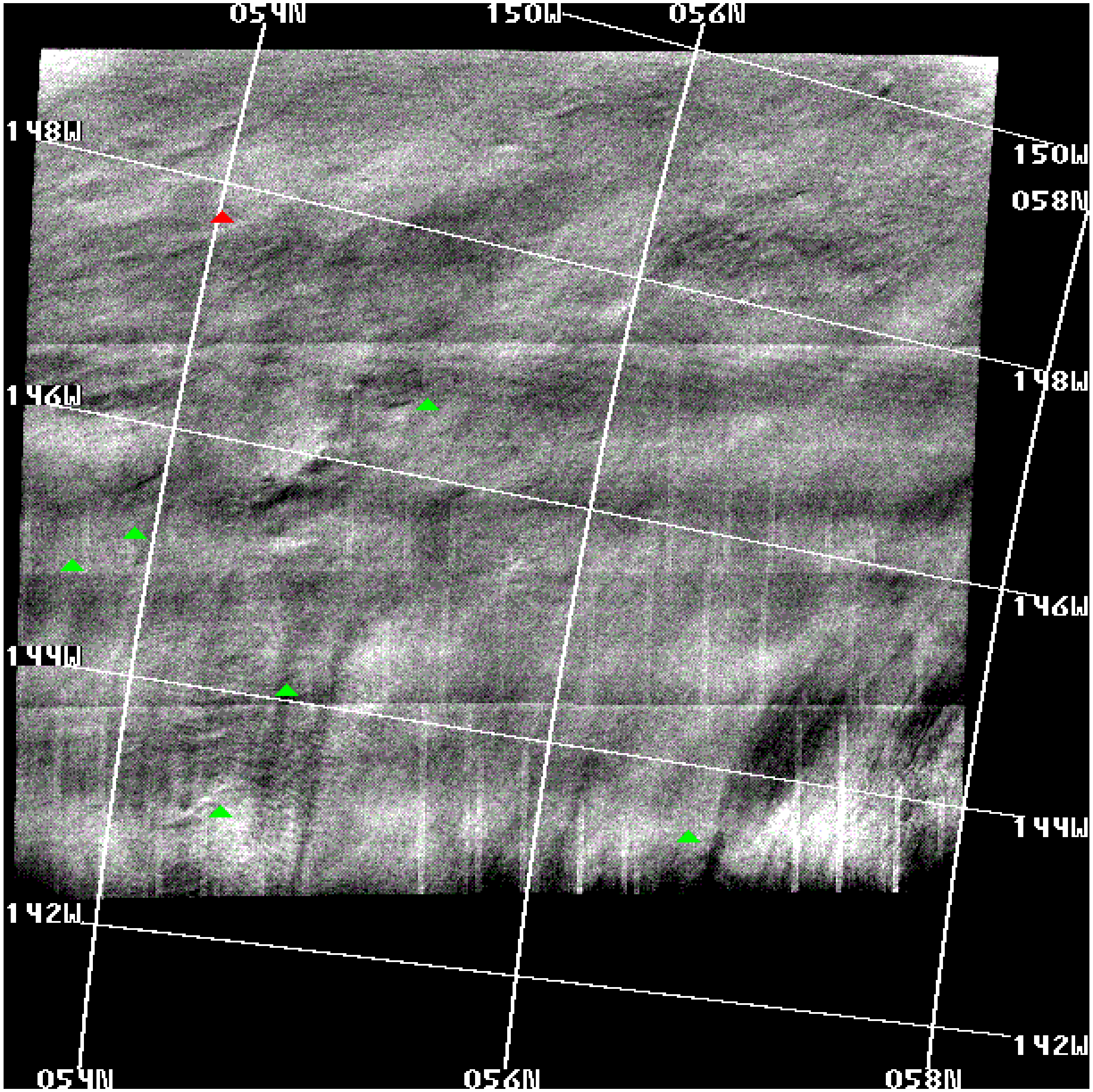
Example Vessel Detection Product



Green is a confident detection, red is a less confident detection. Triangles are in the water, squares are within 2 km of shore.

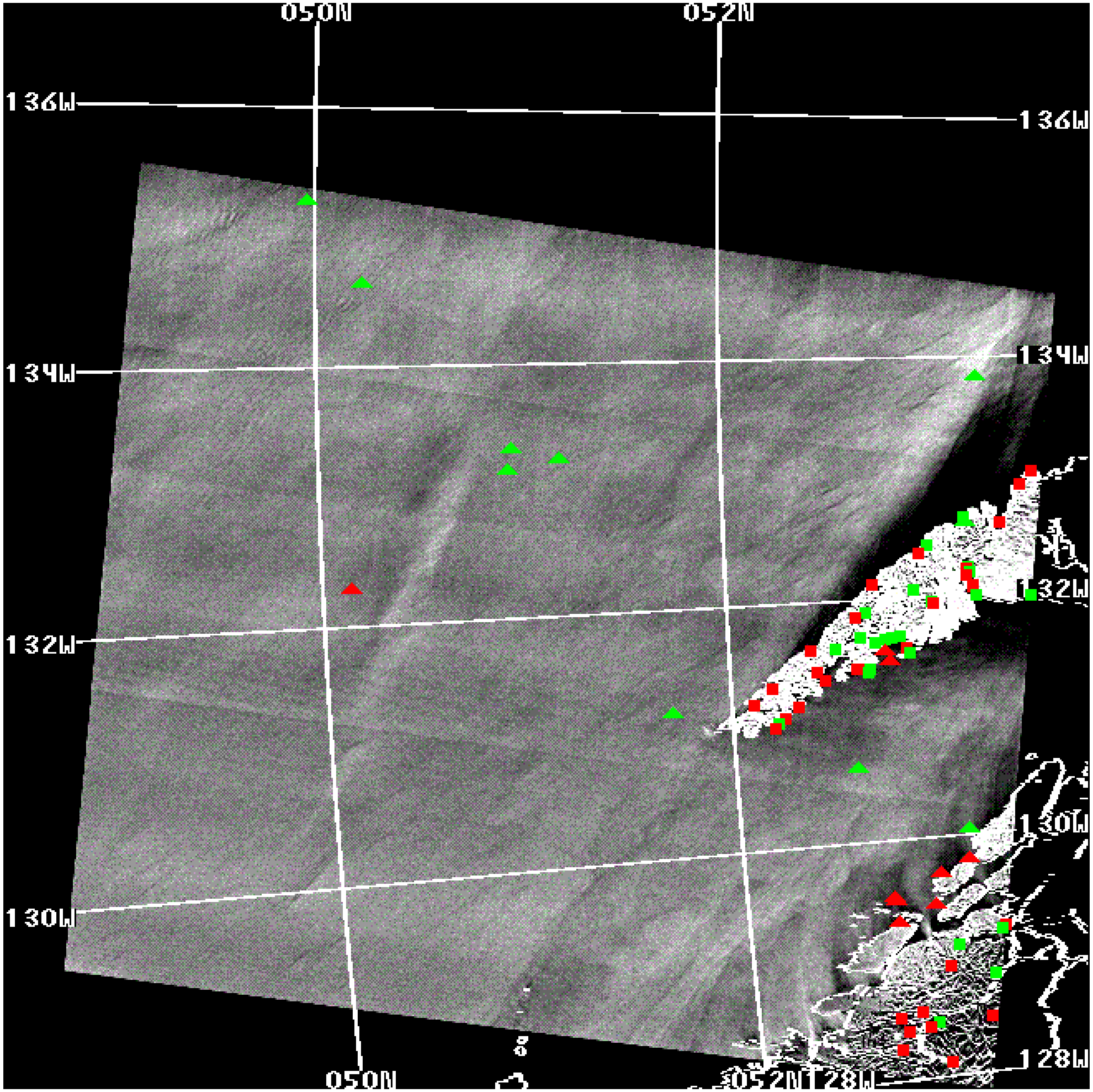
Example Vessel Detection Product

Green is a confident detection, red is a less confident detection. Triangles are in the water, squares are within 2 km of shore.



Example Vessel Detection Product

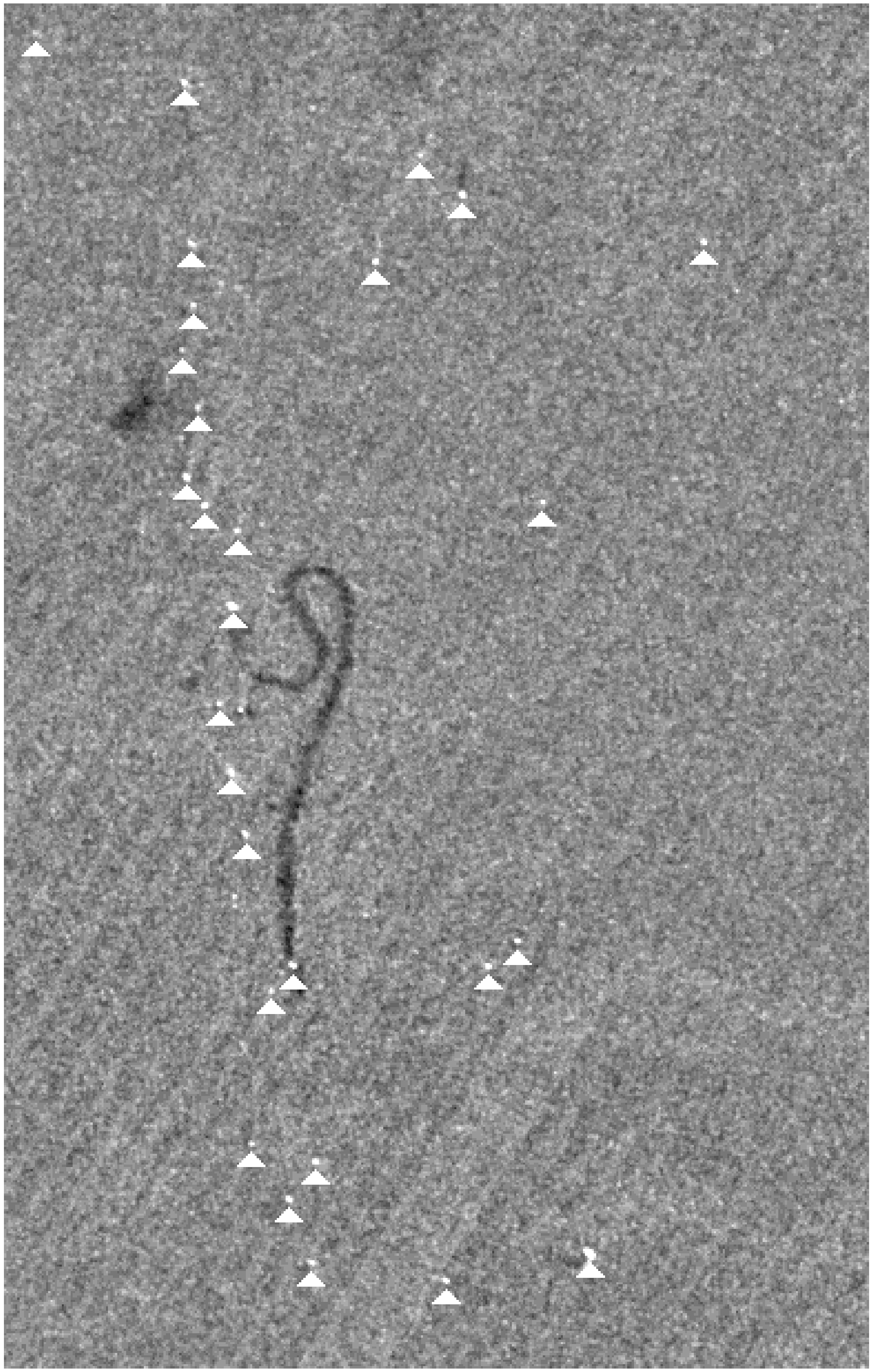
Green is a confident detection, red is a less confident detection. Triangles are in the water, squares are within 2 km of shore.



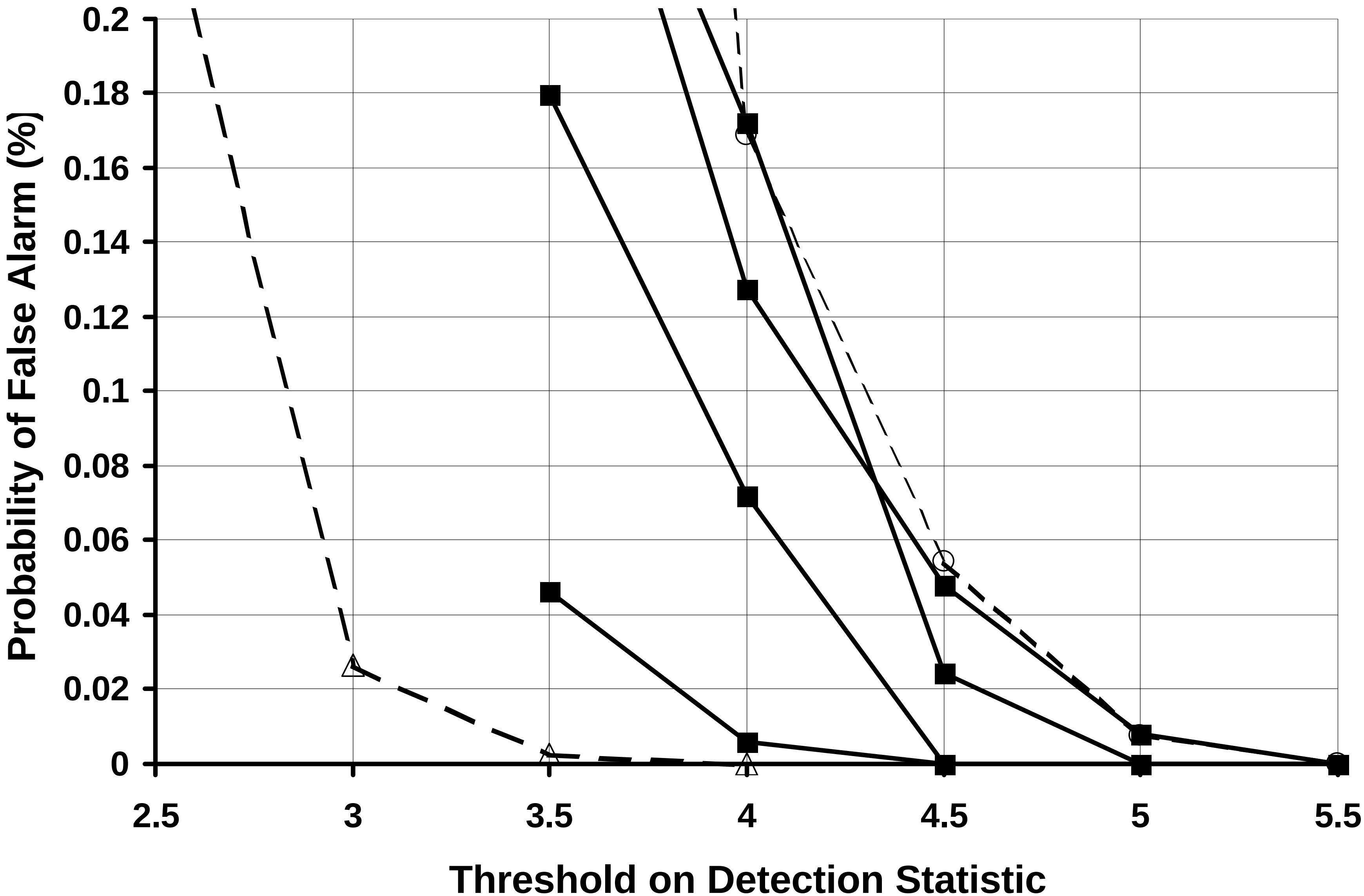
Ship Detection Algorithm Performance Estimation

- A series of 30 RADARSAT images were manually analyzed to determine false alarm rates and obvious missed detections
- An image with a known number of ships was analyzed to determine the number of missed detections and estimate the smallest ship detected
- Images that contained individual ships with known lengths and locations were analyzed

Ship detection results for a fishing fleet. Detections are shown above the white triangles.



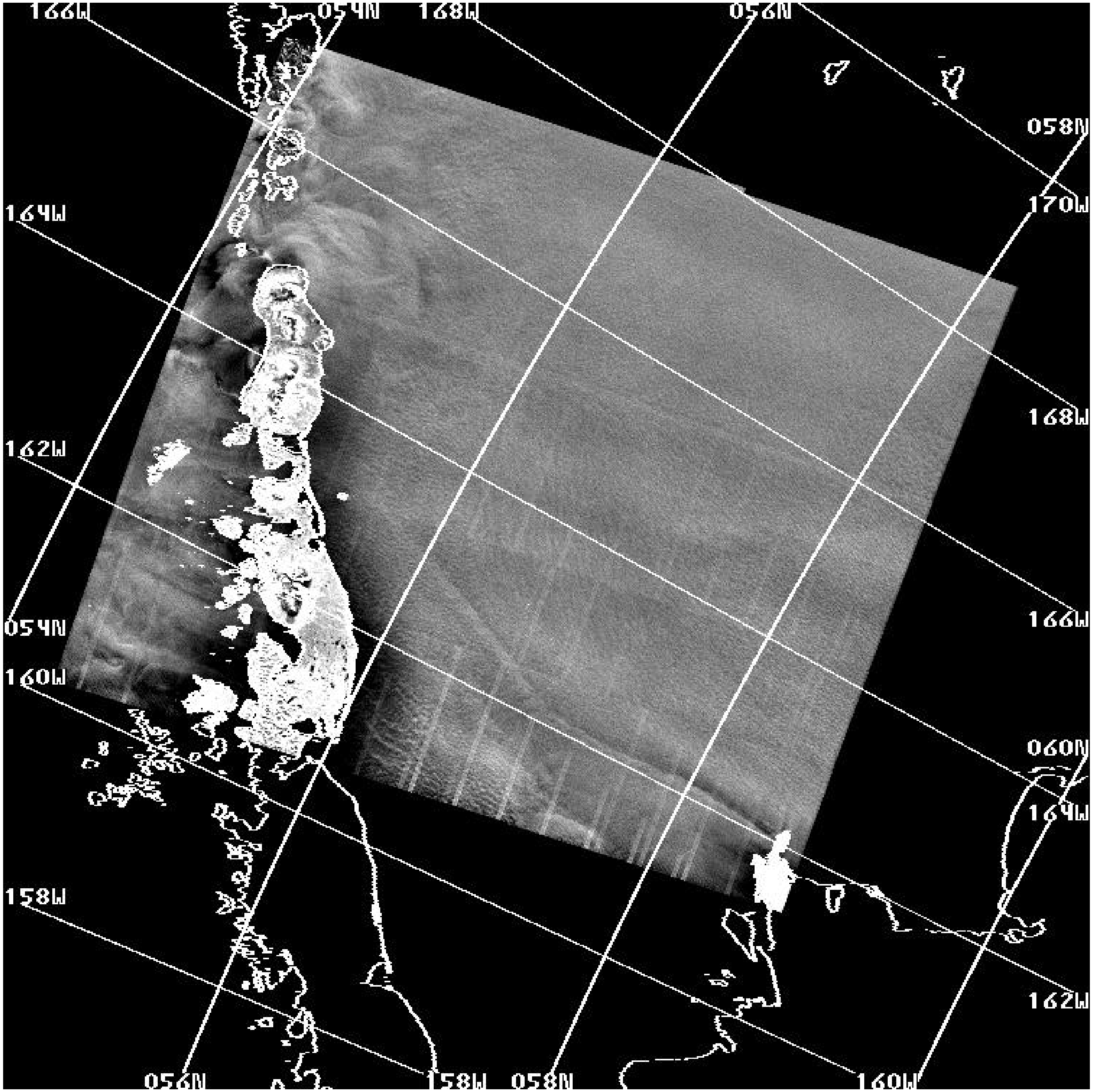
False Alarm Analysis For Various Detection Thresholds



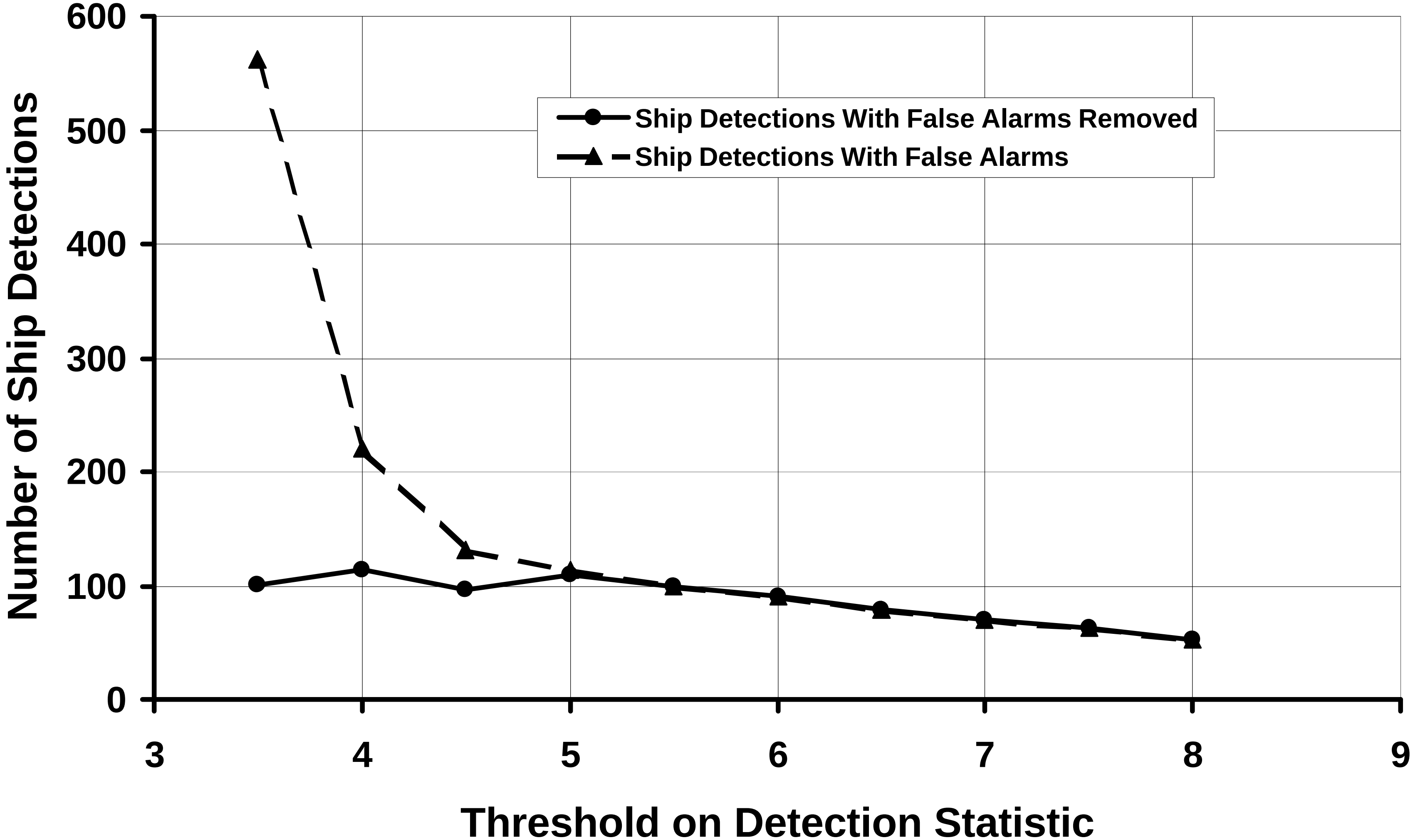
Vessel Detection Algorithm Performance

- A RADARSAT image was collected during the Red King Crab Fishery in Bristol Bay
- The fishery had a known number of ships with a known distribution of ship lengths
- There were no ships in the waters outside of the fishery
- Detections outside of the fishery were used to estimate the false alarm rate, which was then used to remove detections within the fishery that represented false alarms
  - assumes same false alarm rate throughout the image

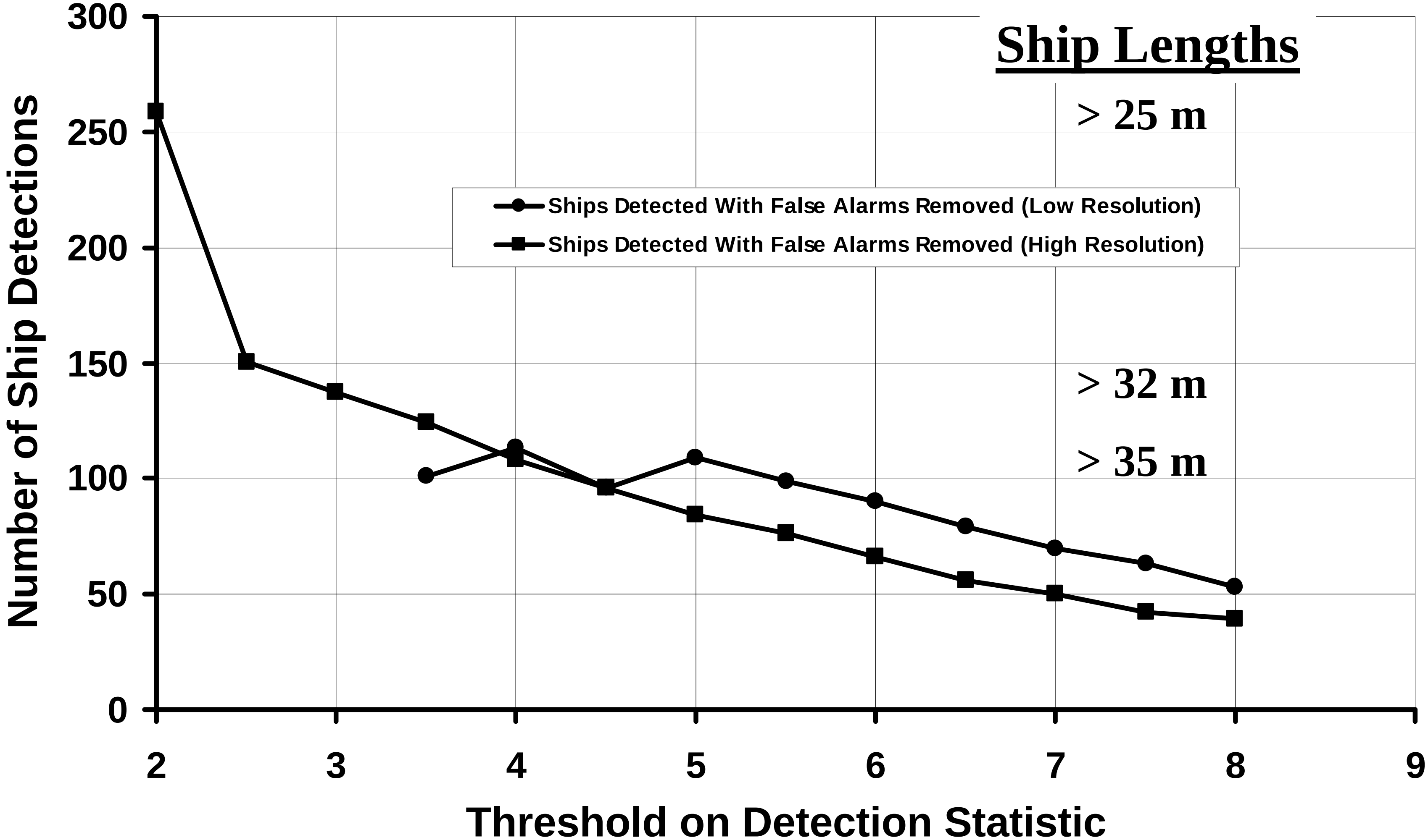
Red King Crab Fishery Image



Detections for the Red King Crab Fishery Using Low Resolution Imagery



Detections for the Red King Crab Fishery With Low and High Resolution Imagery



Estimating The Smallest Detectable Ship

- Assume that the larger the ship, the larger its RCS, and thus the more detectable
- The number of ships that are detected then represent the longest ships in the scene
- Using the known distribution of ship lengths, find the length cut-off for the number of ships detected
  - after removing the estimated number of false alarms

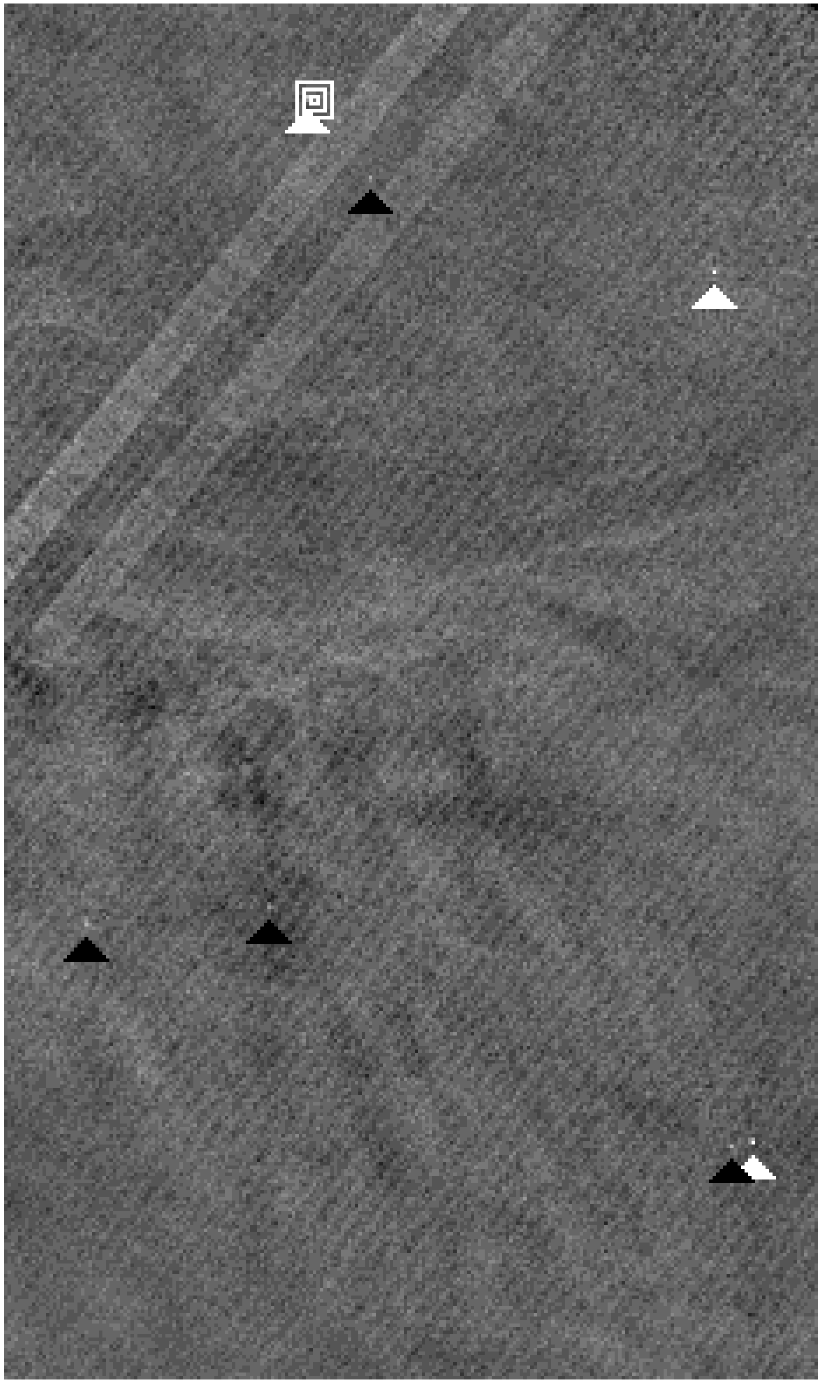
Estimating The Smallest Detectable Ship

- For low resolution (100m sample spacing) imagery
  - ships detected > 35 meters in length (0.01% FAR)
  - appears to be limited by sample spacing (false alarm rate is still low when number of detections plateaus)
- For high resolution (50m sample spacing) imagery
  - almost all the ships can be detected, but with unacceptable false alarm rates
  - for reasonable false alarm rates, ships detected > 32 meters in length (0.002% FAR)
  - limited by false alarm rate, not sample spacing

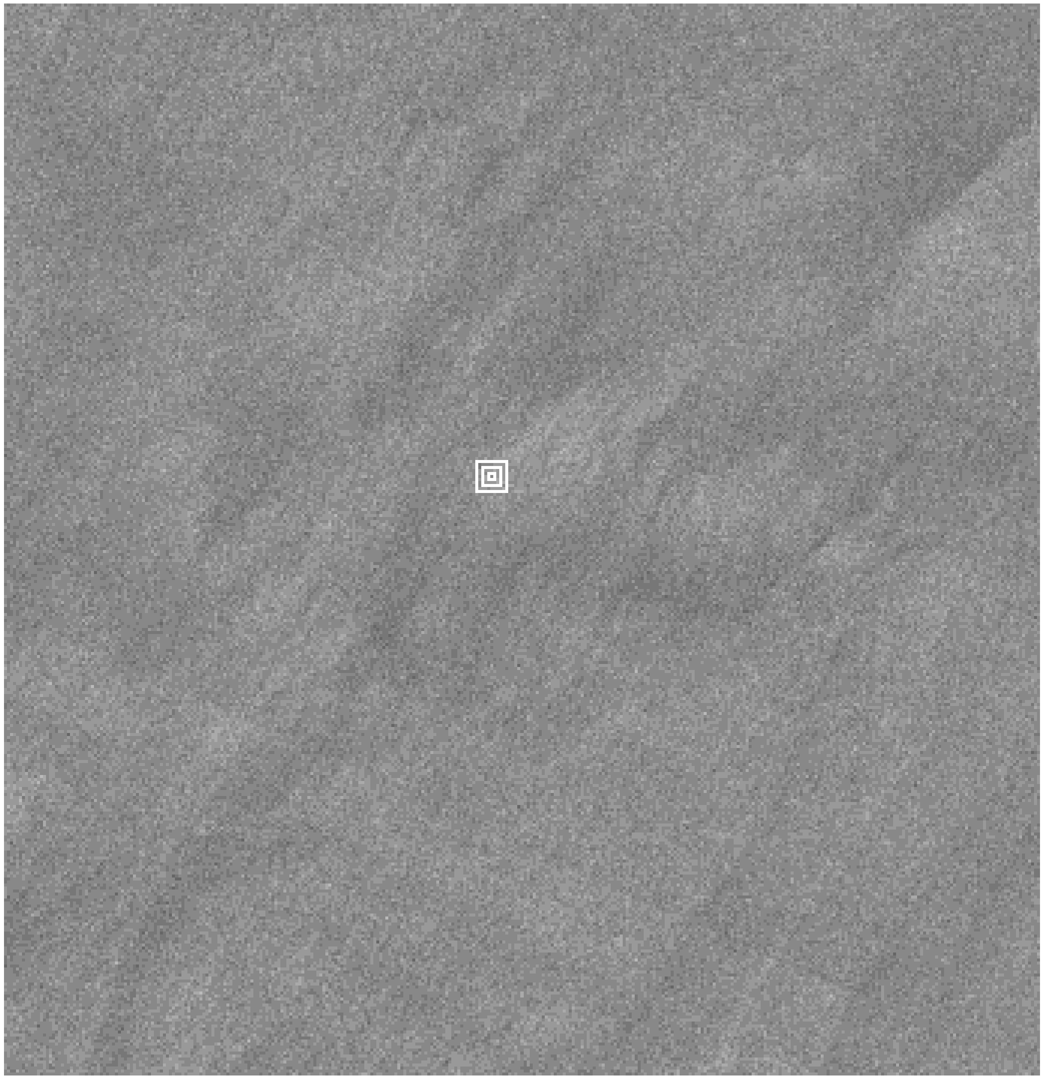
Vessel Detection Algorithm Performance

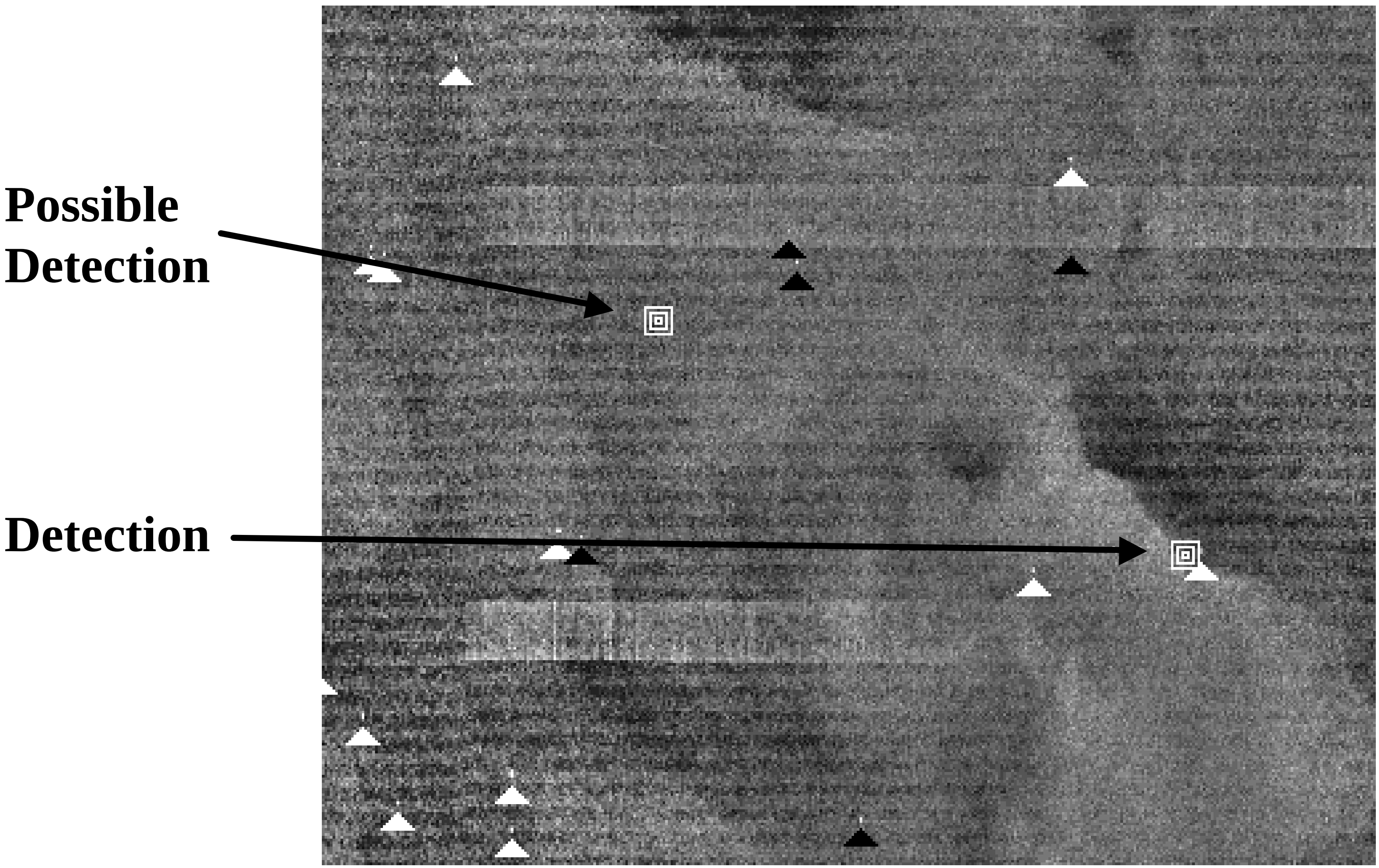
- **For a small number of ships (6), their locations were known at specific times**
- **RADARSAT images were located that should contain the ships and processed with the detection algorithm**
- **Results were put into three bins:**
  - ***detection* => ship location very near a detection**
  - ***possible detection* => ship location close to a detection**
  - ***missed detection* => no ship detection nearby the ship location**

Example of a detection: nested white squares show reported ship location. White triangles represent “sure” detections, black triangles are “maybe” detections



Example of a missed detection




Possible Detection
Detection

Results for Individual Ships

Ship Length (meters)	Possible Number of Detections	Number of Detections	Number of Possible Detections	Number of Missed Detections
55	4	4	0	0
55	2	1	1	0
49	2	2	0	0
47	3	1	1	1
41	1	0	0	1
32	1	0	0	1

=> ships detected if length > 41 meters

Summary of Vessel Detection Algorithm Performance

- Low Resolution Images (100 meter sample spacing)
  - Vessels detected if length > 35-41 meters
    - limited by sample spacing
  - False Alarm Rate (FAR) 0.02% per detection attempt
- High Resolution Images (50 meter sample spacing)
  - Vessel detected if length > 32 meters
    - limited by FAR
  - FAR = 0.002% per detection attempt

Future Work For Vessel Detection Algorithm

- Incorporate approach that will allow the signal box to vary in size to handle large and small ships simultaneously
  - use a large number of nested boxes, pick the signal/background pair that maximize d
- Ice in the image causes a significant number of false alarms
  - develop an automated algorithm for detecting ice
  - need to separate types of ice in order to still locate vessels within ice “fingers”

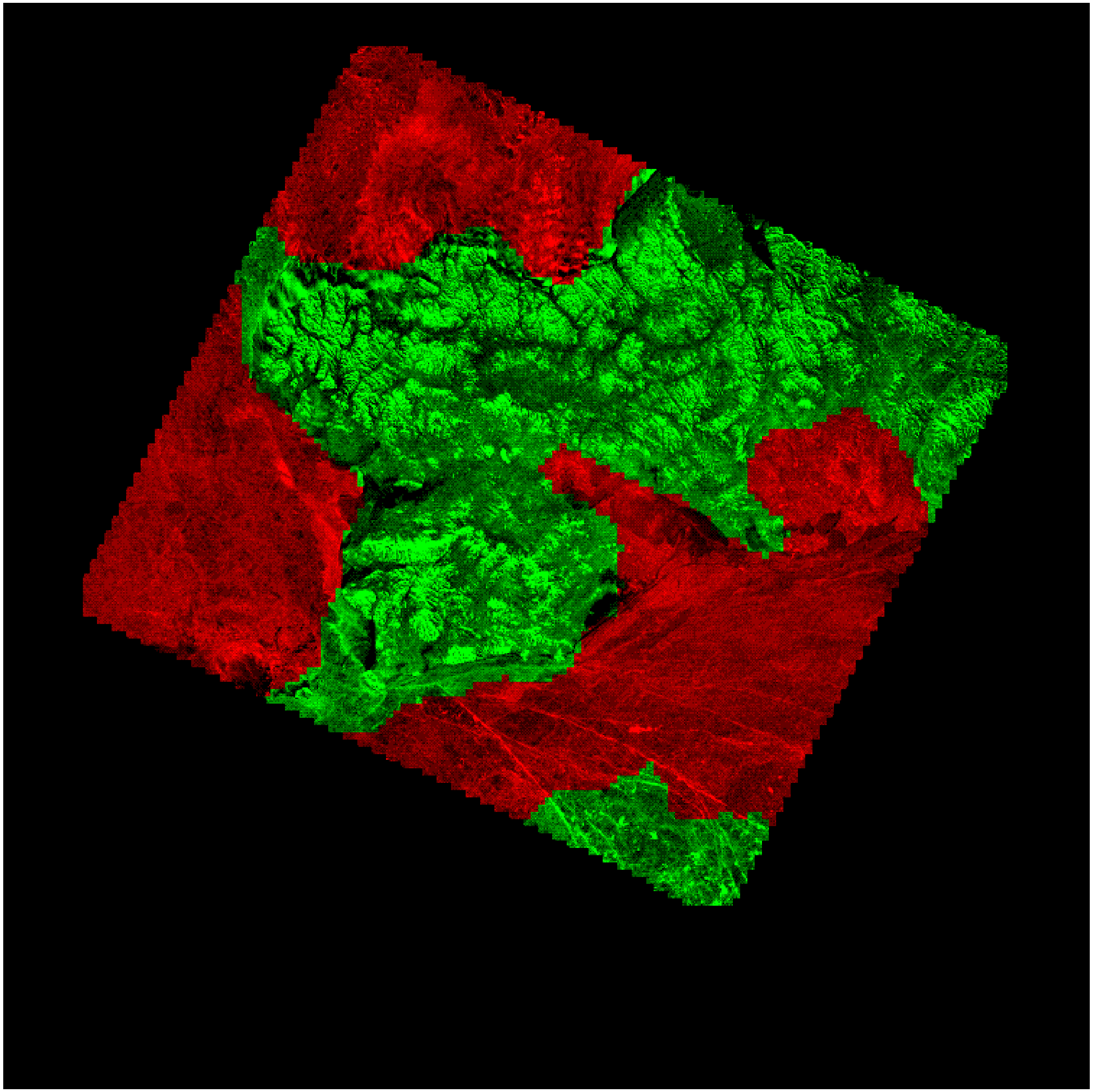
Example product for automated ice classification:

green = land

red = ice

yellow = ice fingers

blue = water



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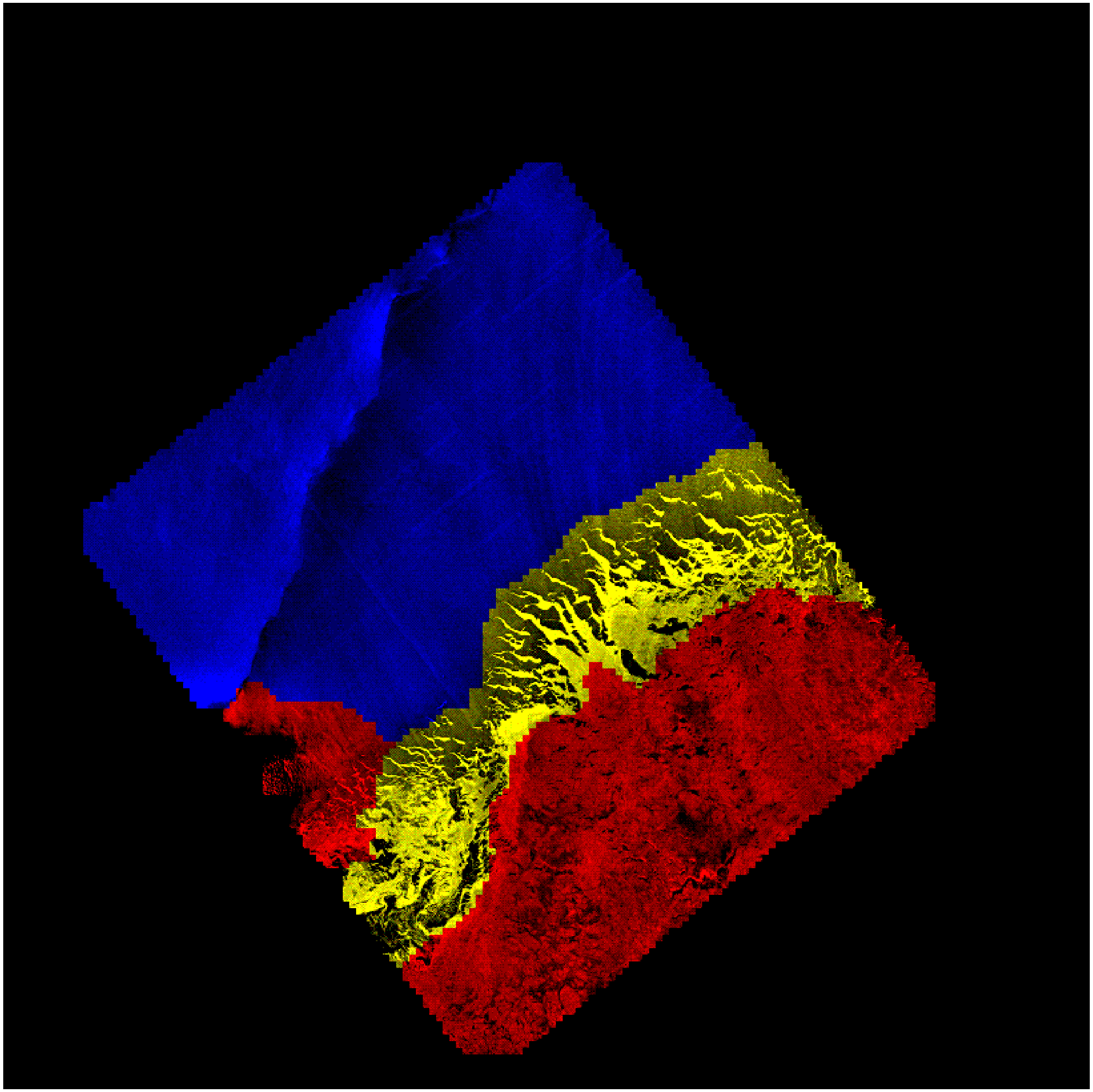

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